Assessing the effects of freshwater inflows and other key drivers on the population dynamics of blue crab and white shrimp using a multivariate time-series modeling framework: Phase 2

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Phase 1 summary

- Data from the Texas Parks and Wildlife Department (TPWD) Coastal Fisheries monitoring program, U.S. Geological Survey (USGS) flow gage stations, and several other sources were acquired for 1982–2013
- Drivers of blue crab and white shrimp population dynamics were assessed using multivariate autoregressive (MAR) models
- Detected significant lagged effects of predators, water temperature, salinity, and river discharge on the abundances of both focal species
- Effects of freshwater inflows on focal species abundances must be assessed in conjunction with other drivers at time lags of up to two years

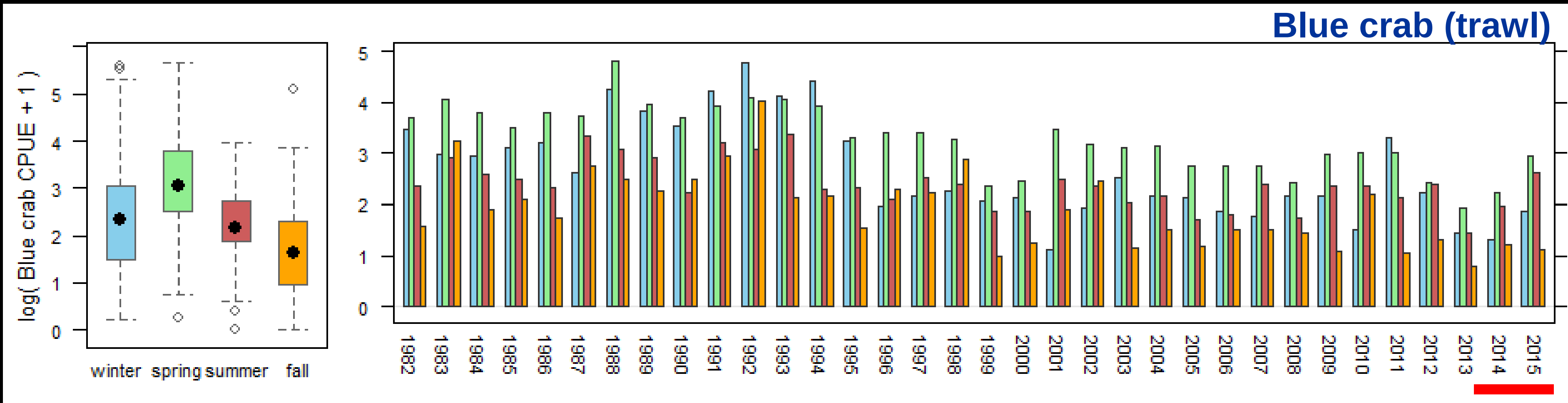
Phase 2 Tasks

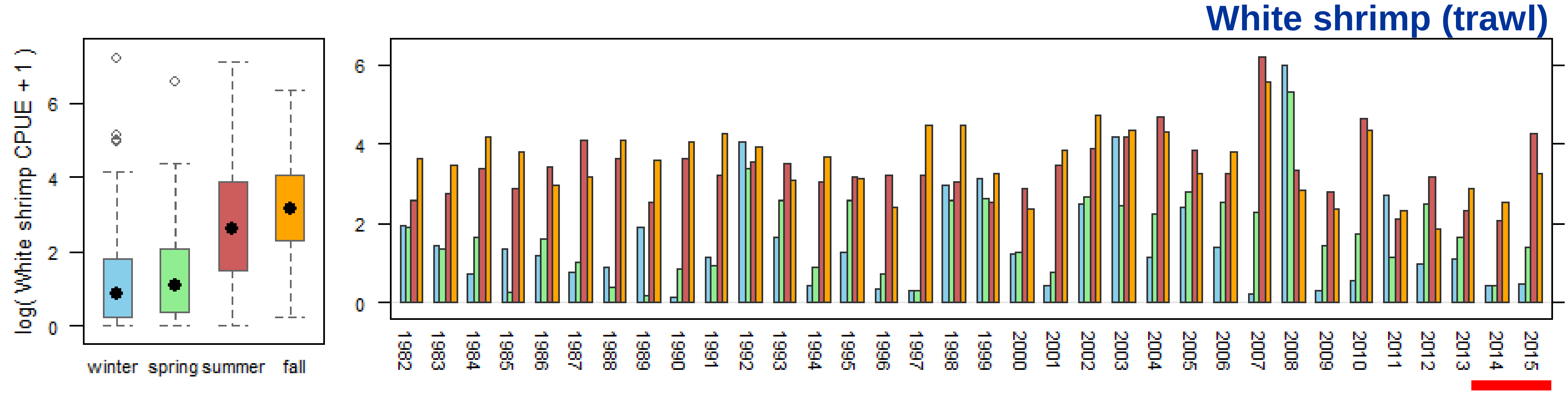
- ✓ Update datasets and rerun original models
- ✓ Reformat datasets to reflect TCEQ inflow standard seasonal increments
- ✓ Run new sets of MAR models using reformatted data
- ✓ Assess whether particular seasons are more influential on focal species abundances
- ✓ Model adaptation for inflow scenario assessment
- ⟶ Prepare & submit final report
- • Submit data and annotated R code

Updated Data

Seasonal divisions:

Winter (Jan-Mar) **Spring (Apr-Jun)** **Summer (Jul-Sep)** **Fall (Oct-Dec)**





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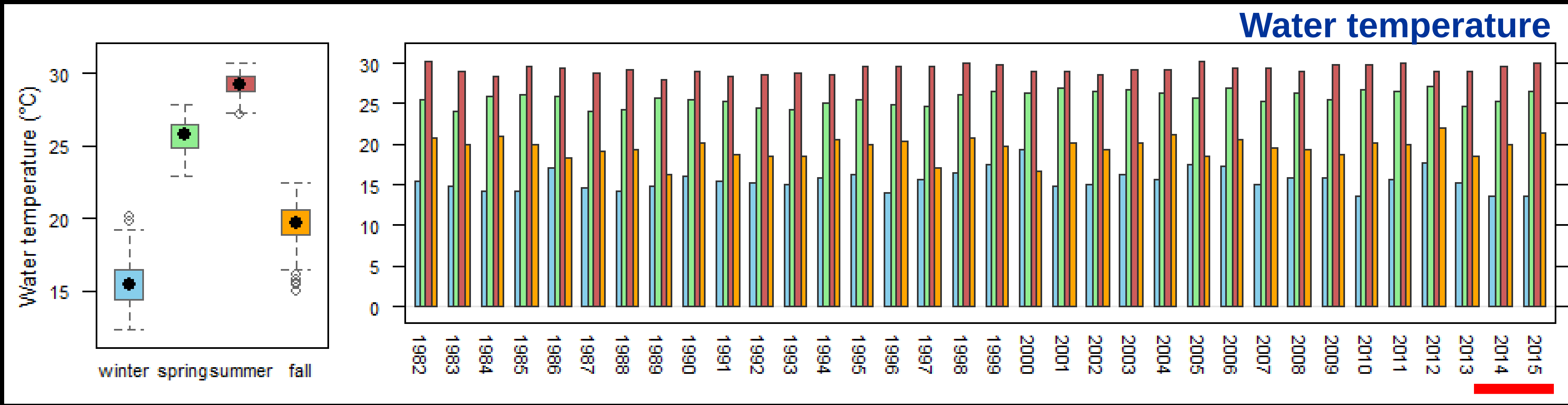
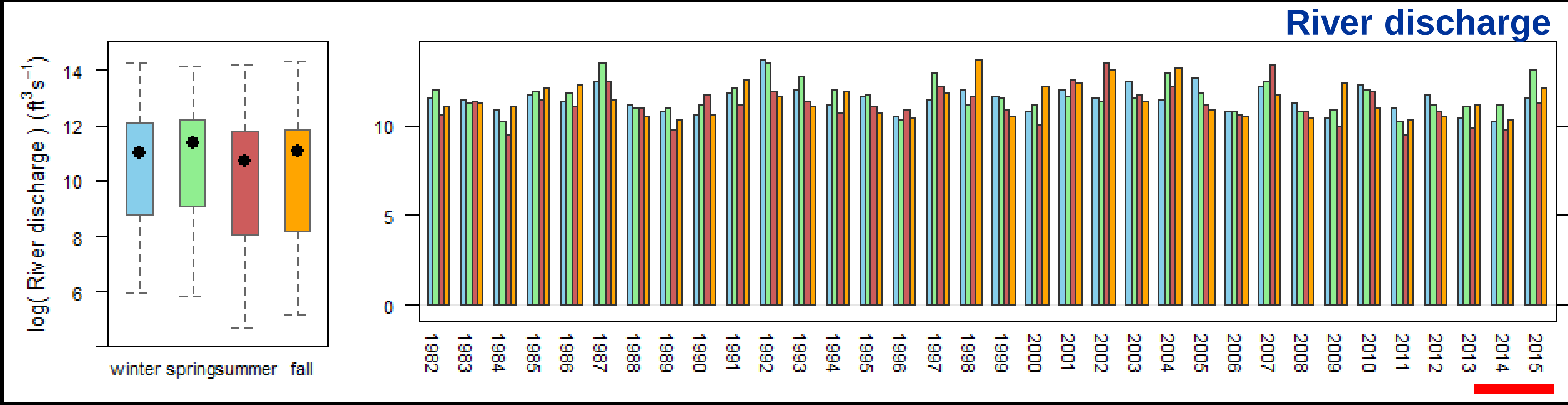
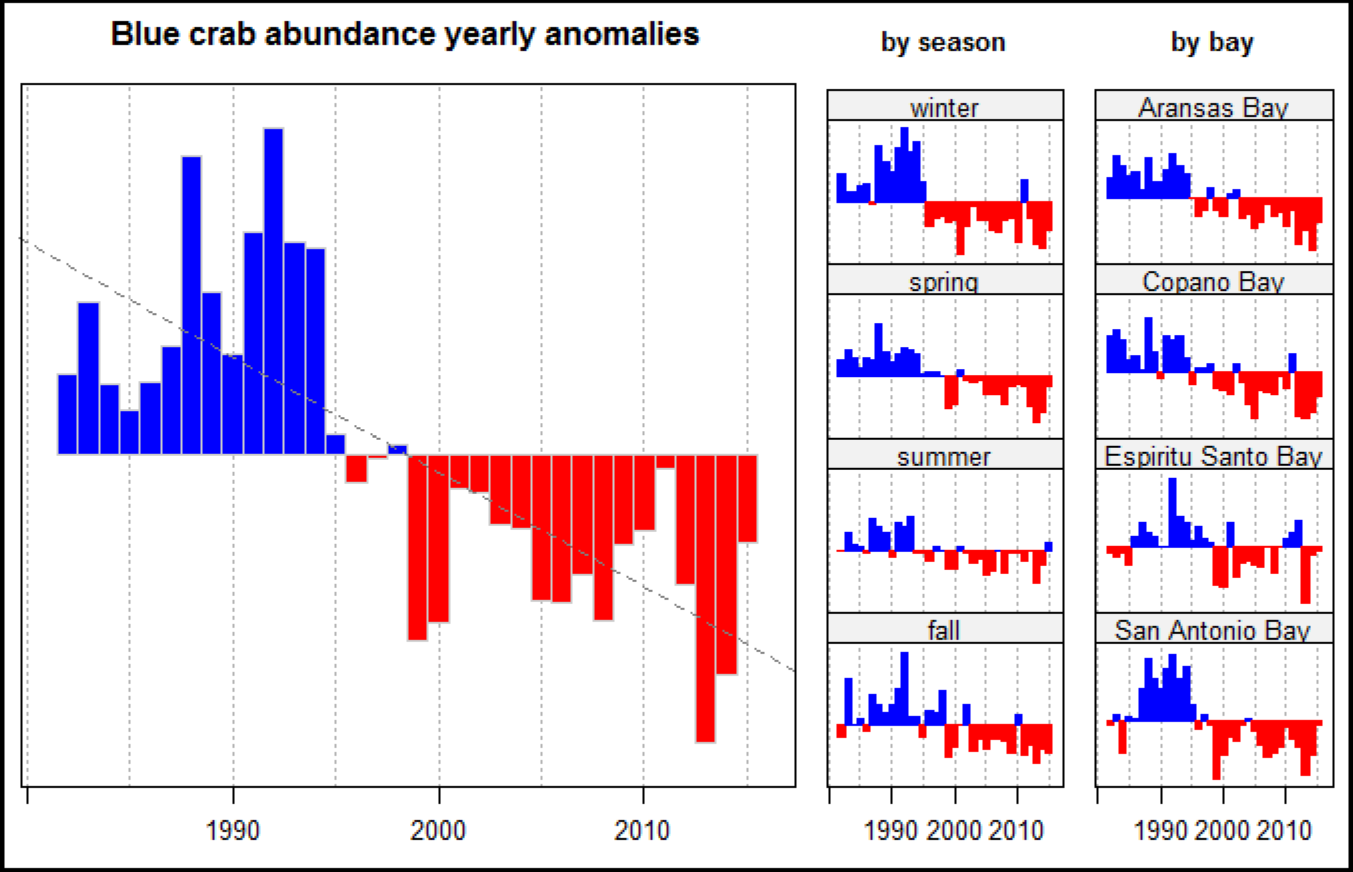
Winter (Jan-Mar)   Spring (Apr-Jun)   Summer (Jul-Sep)   Fall (Oct-Dec)





Updated Data

Deviations from mean value (anomalies)



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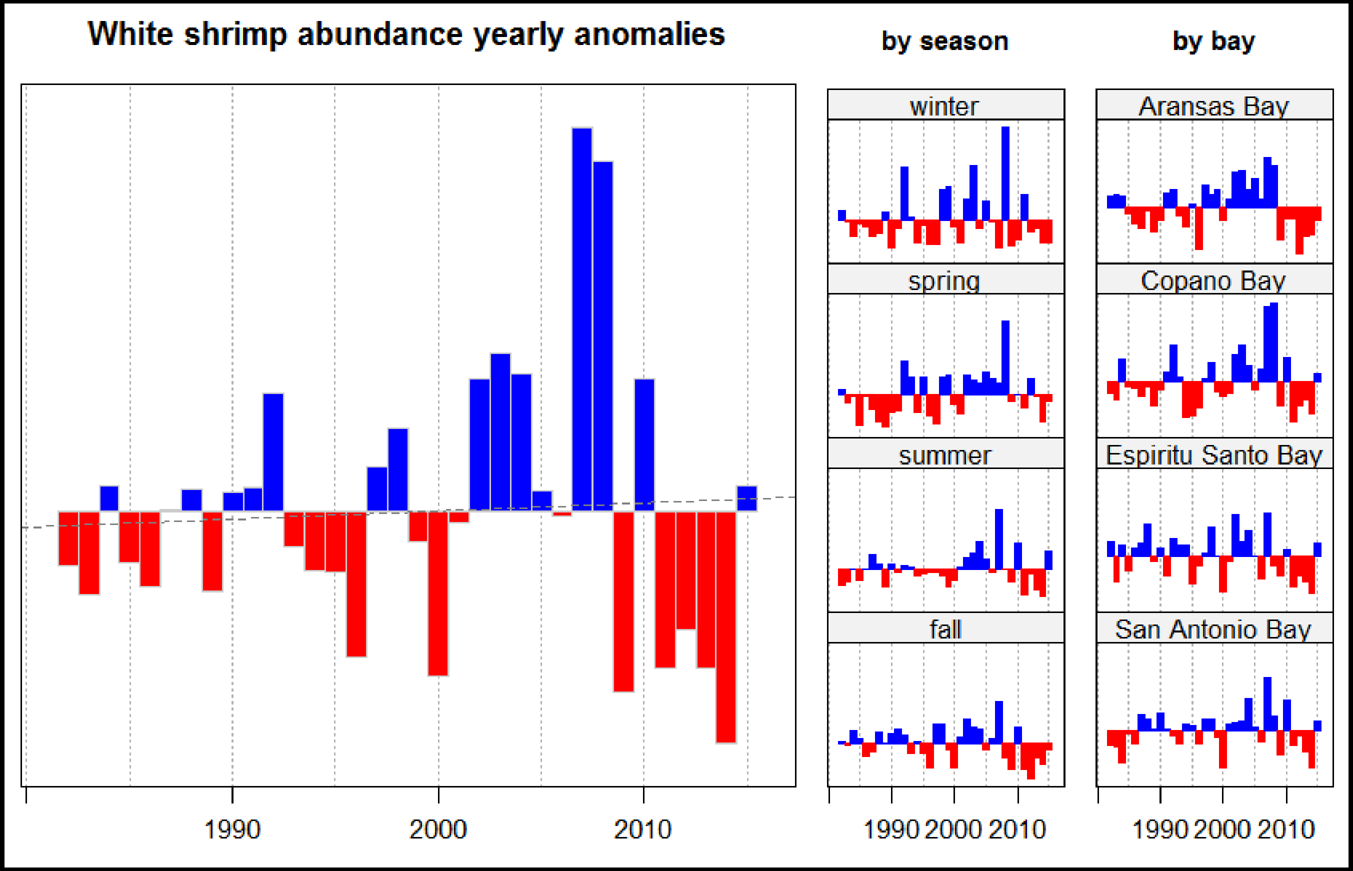

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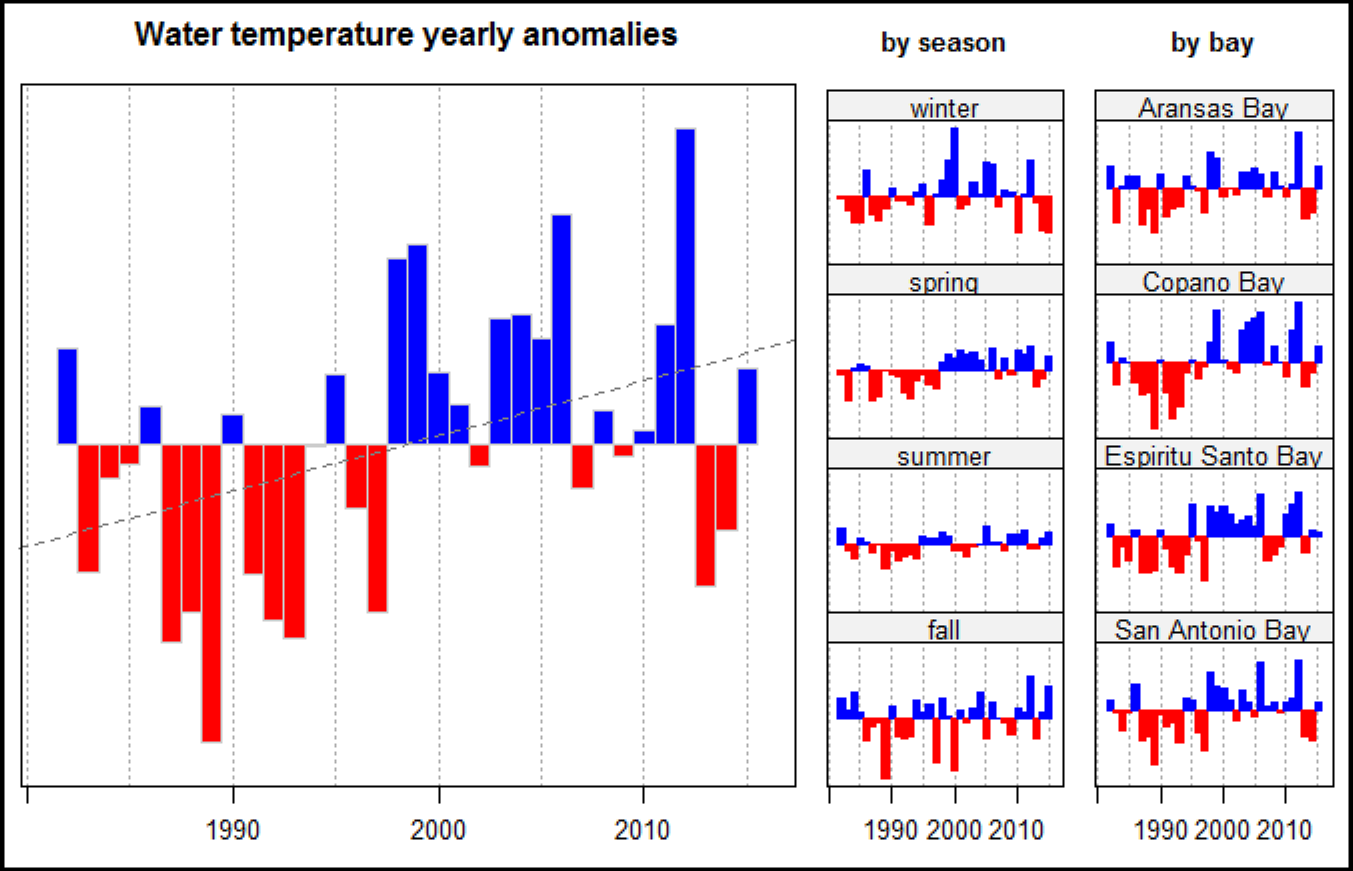

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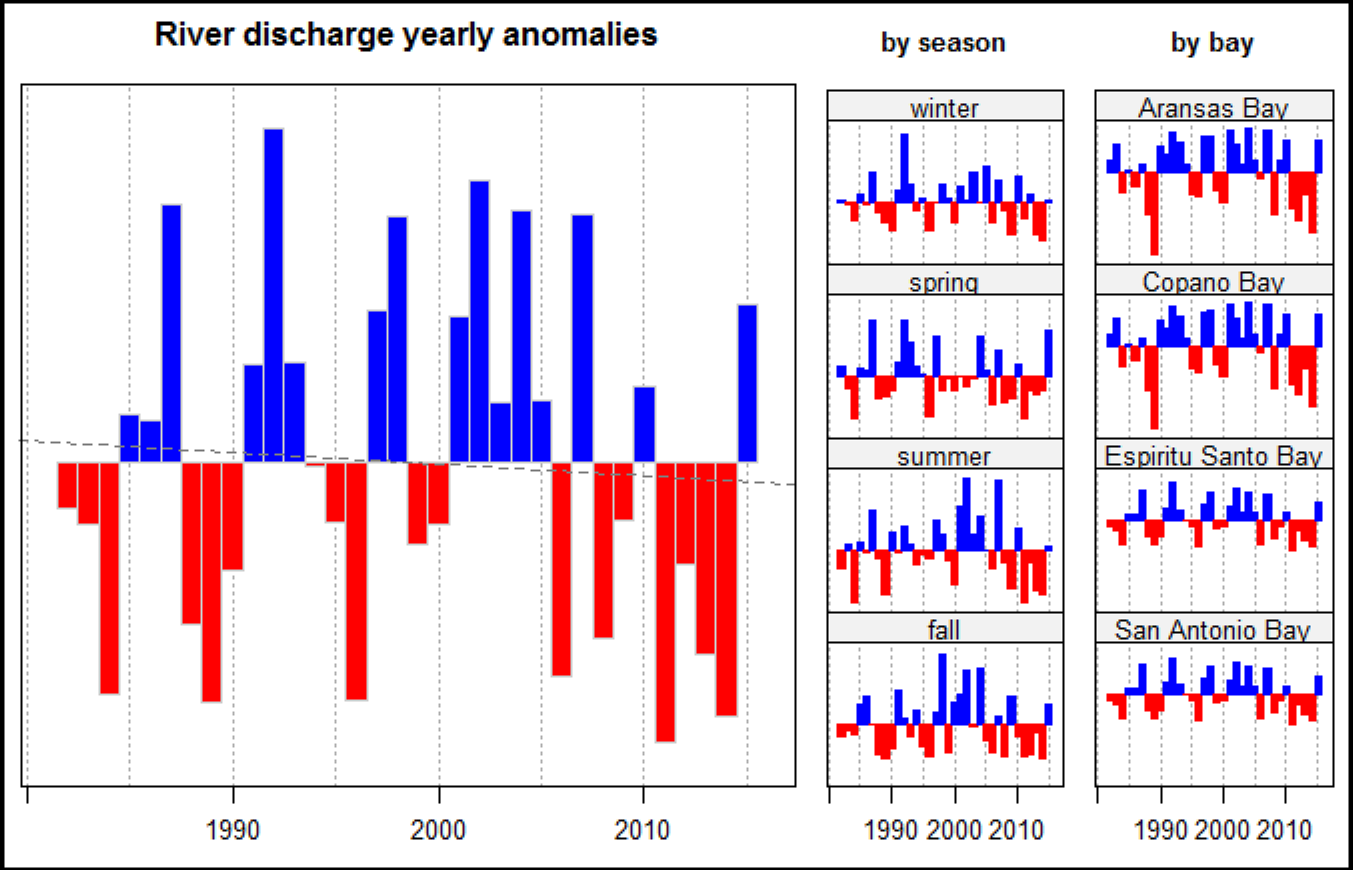
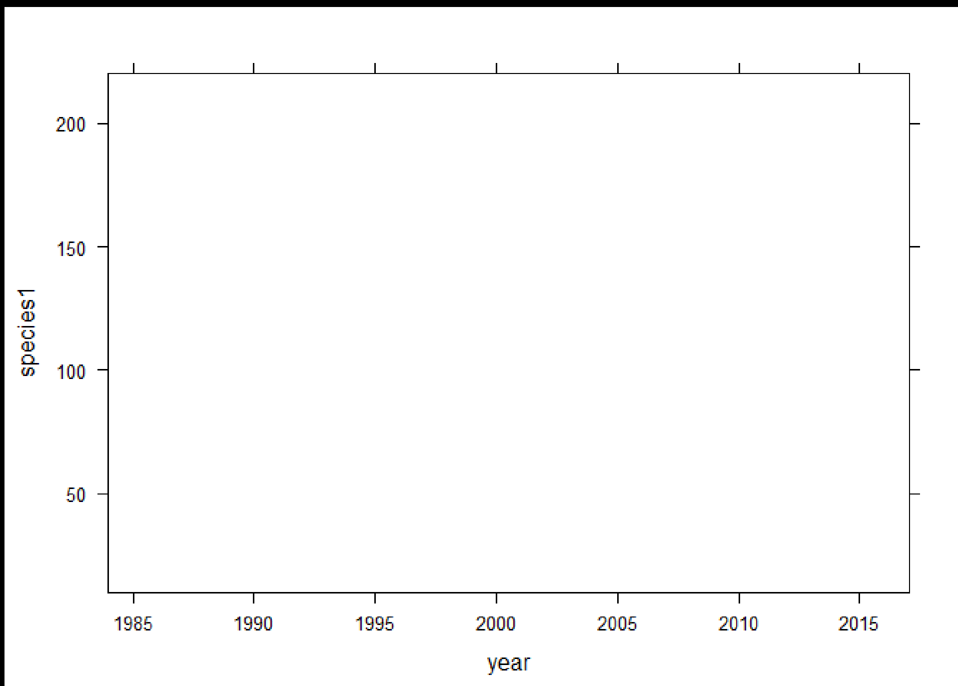
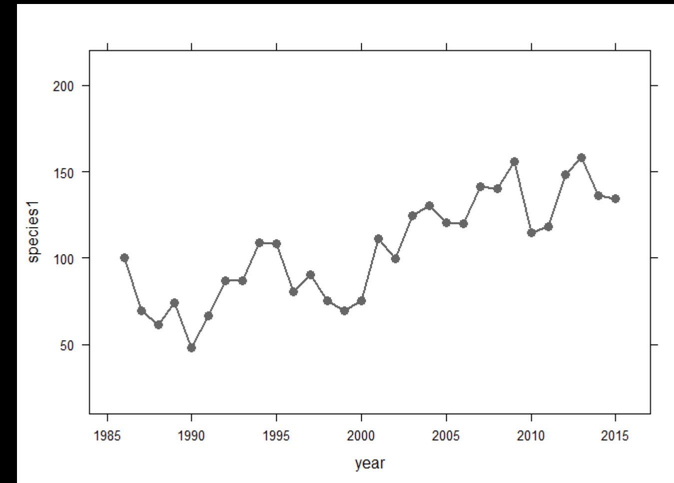
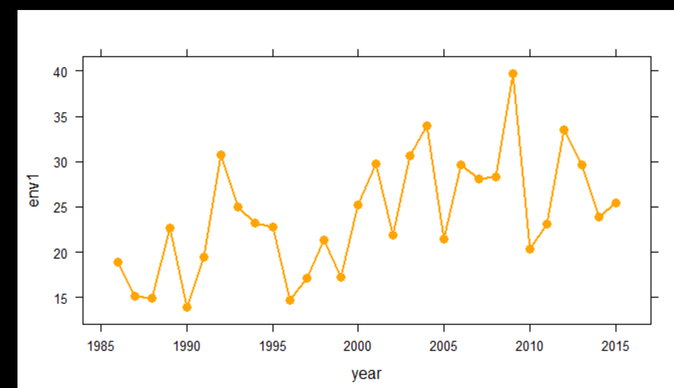


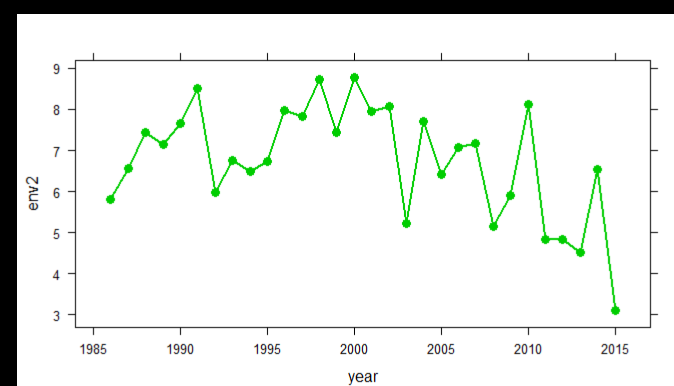
MAR models

Example: no auto-regression









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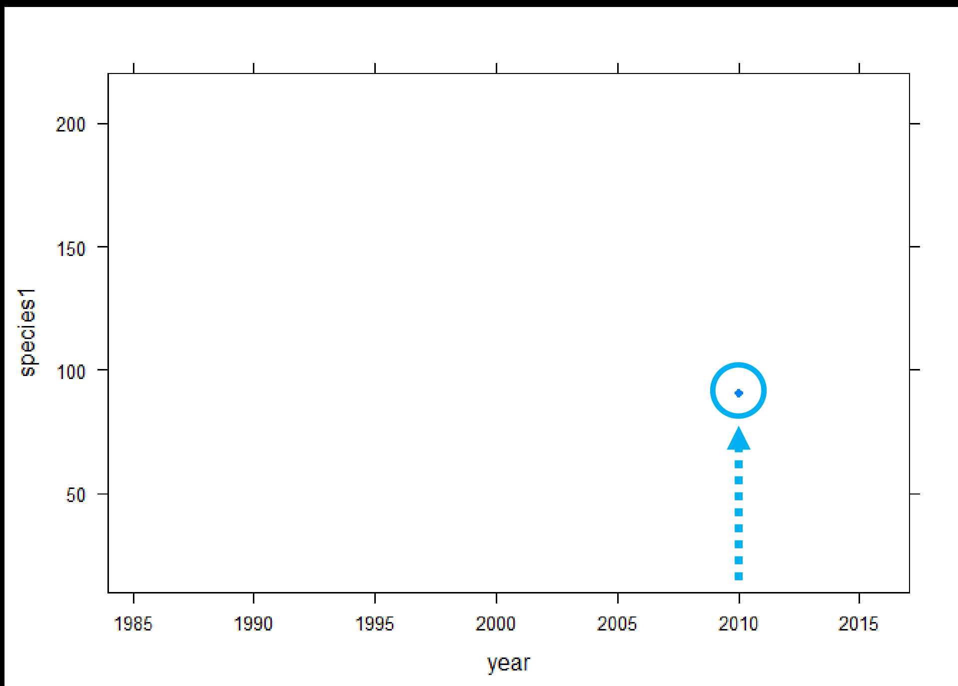

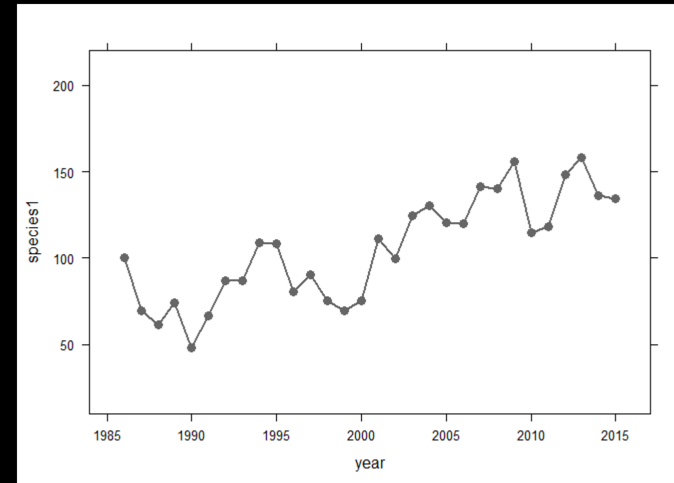

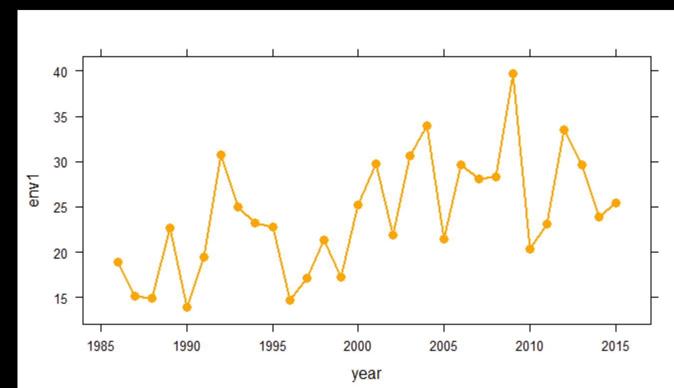

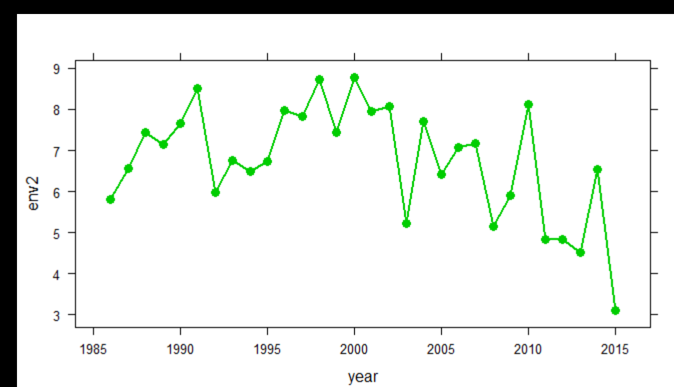

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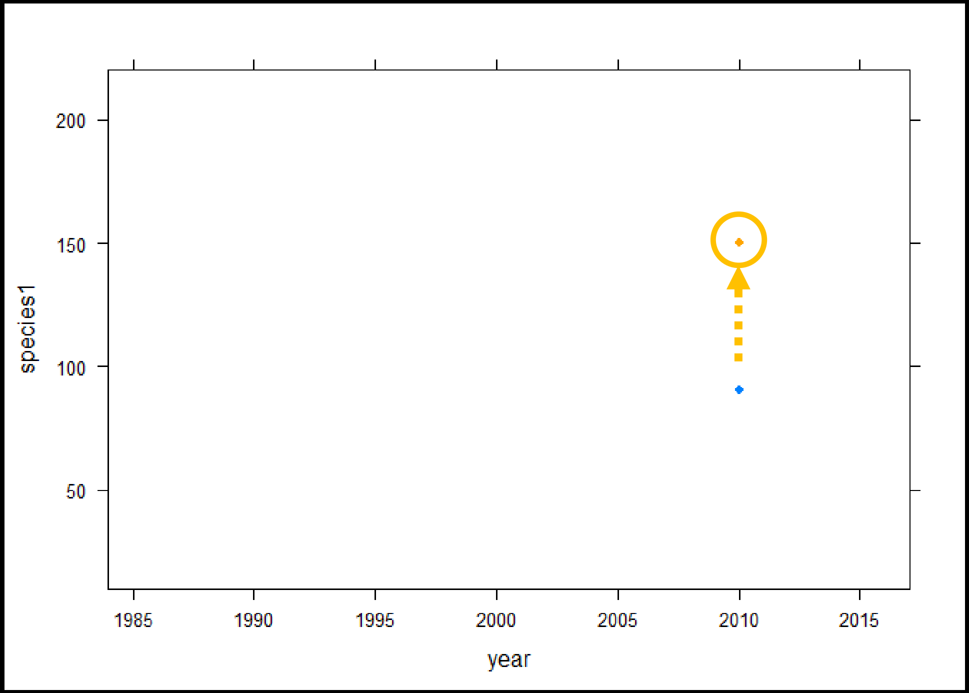

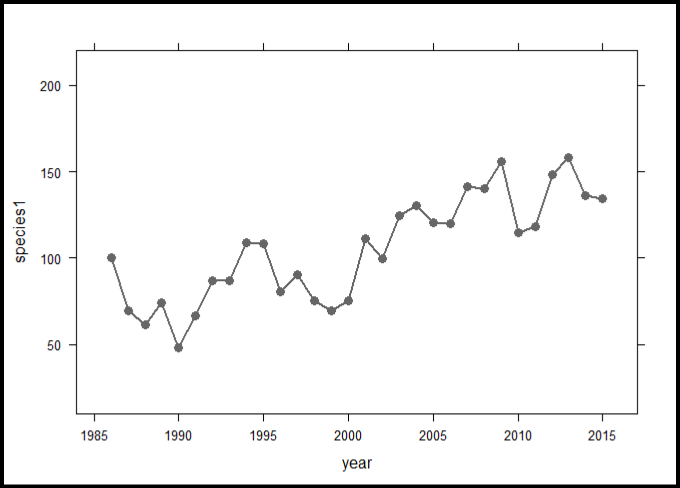

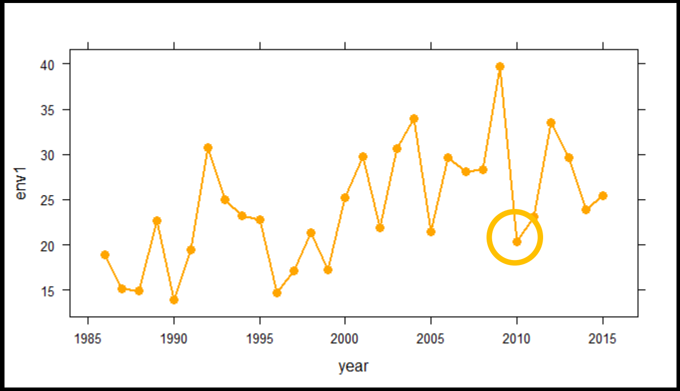

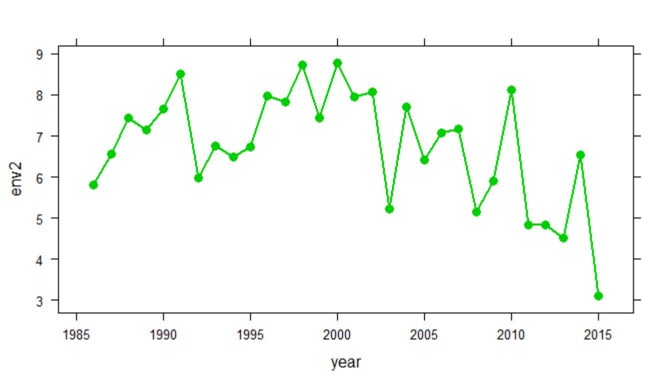

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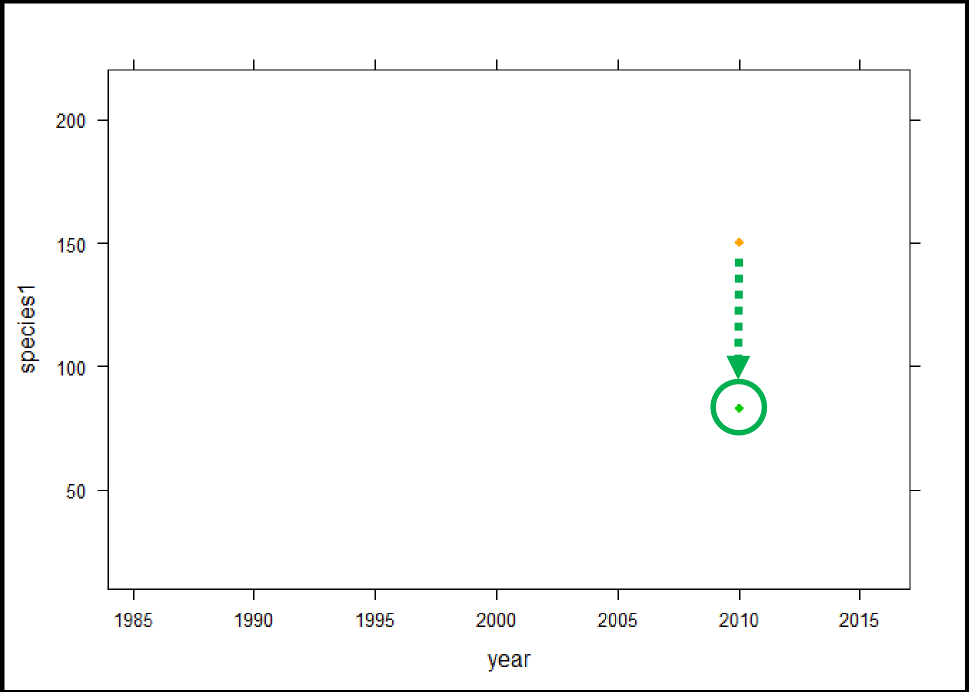

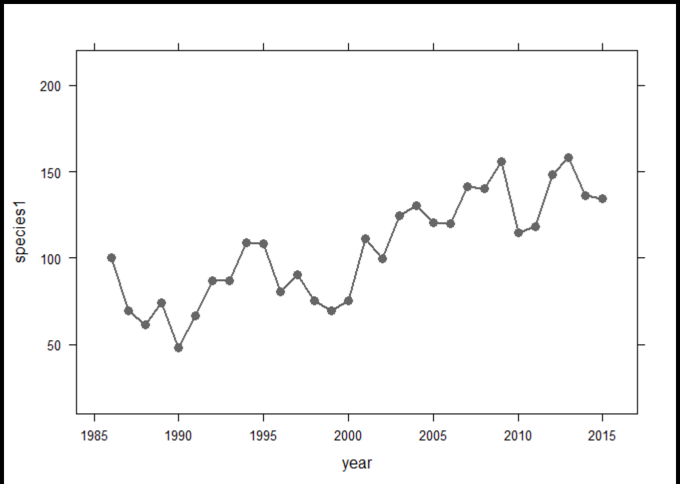

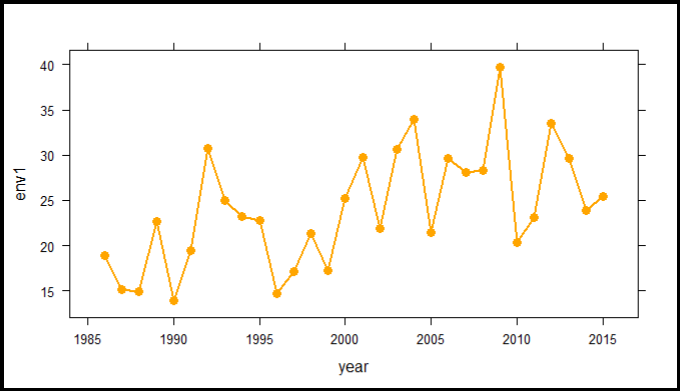

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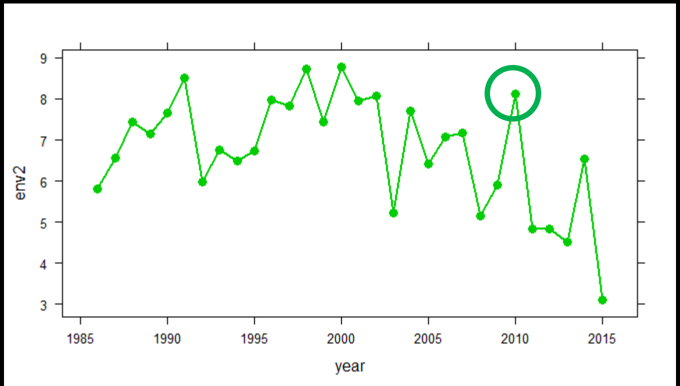

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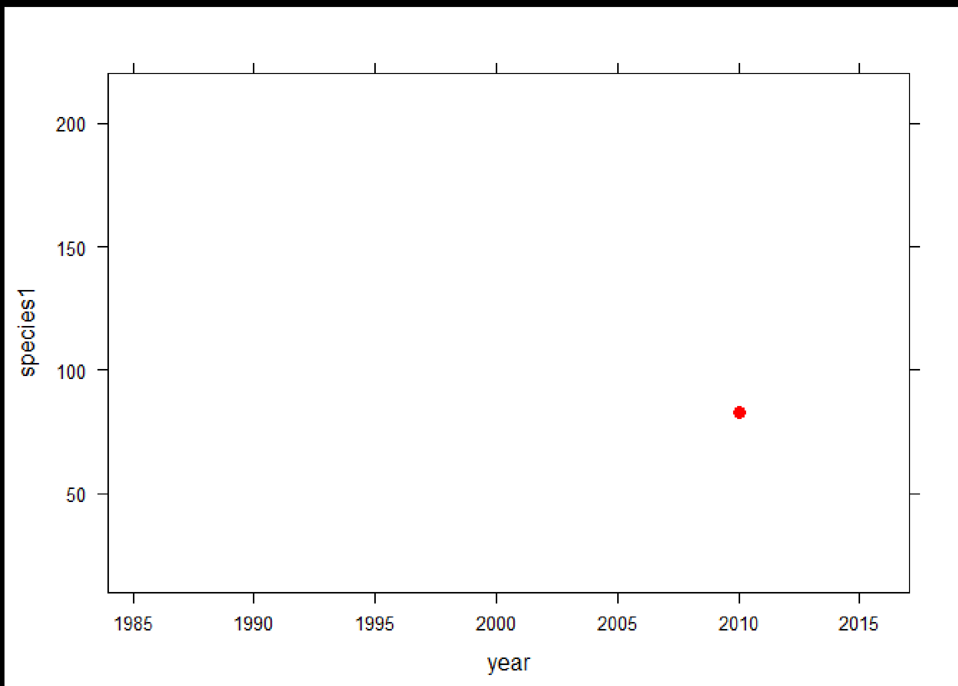

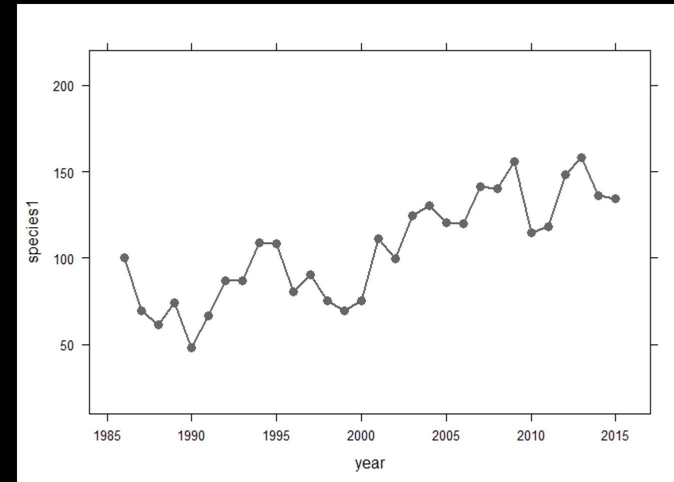

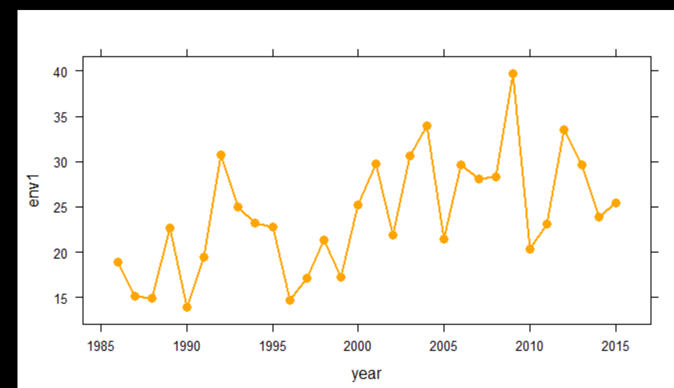

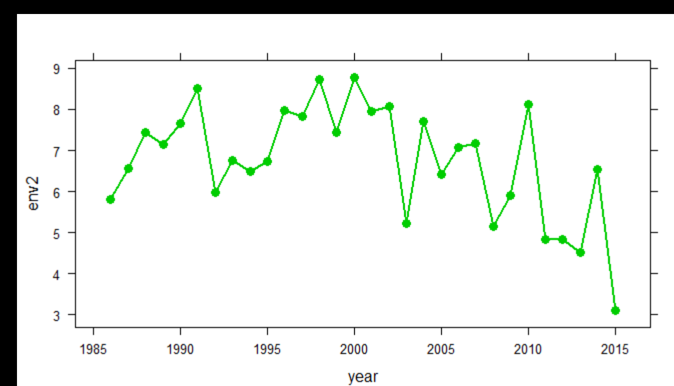

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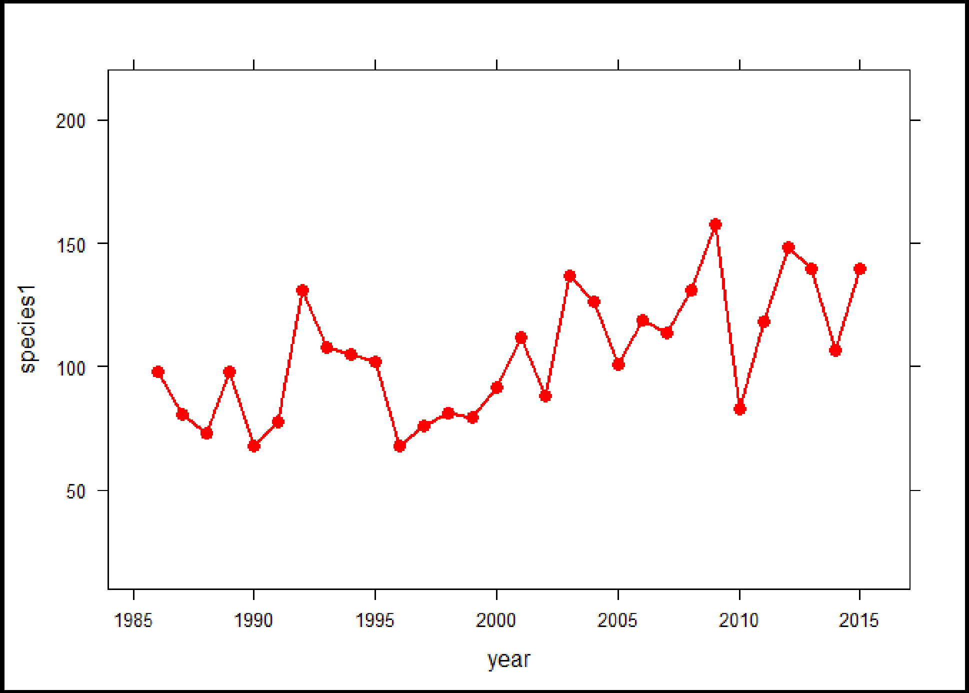

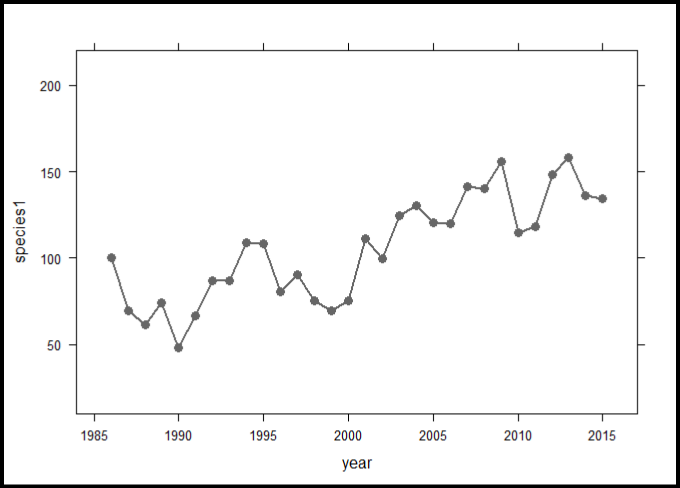

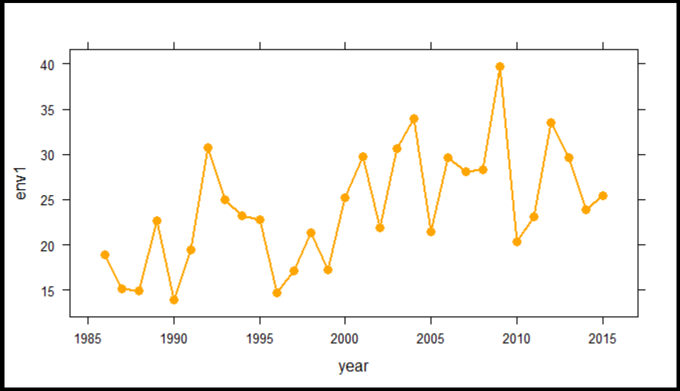

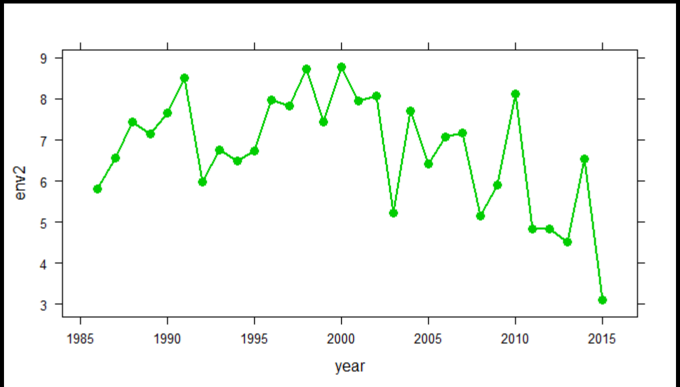

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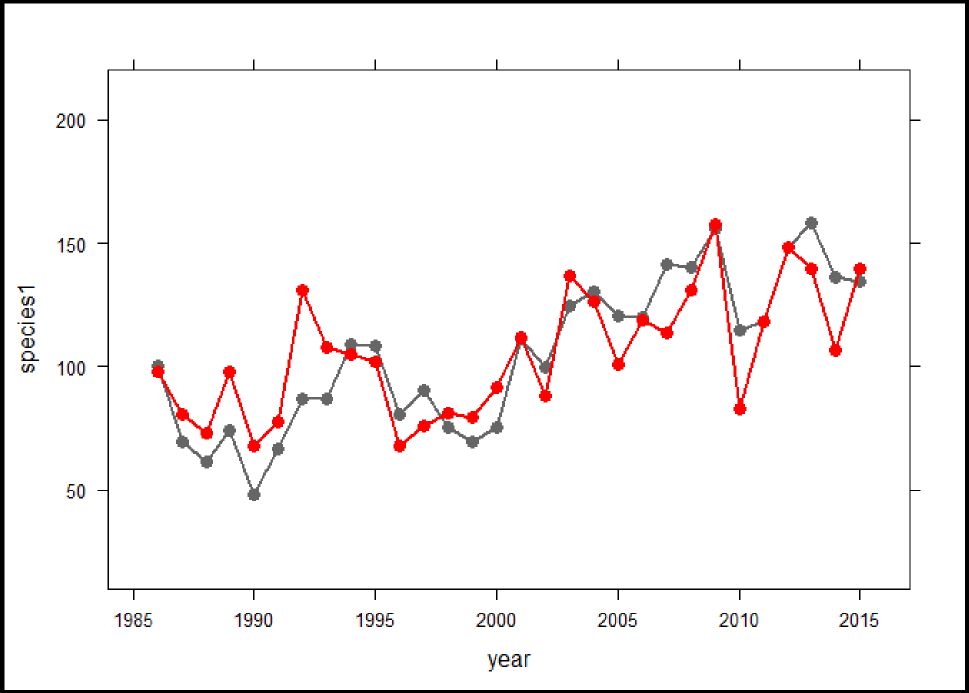

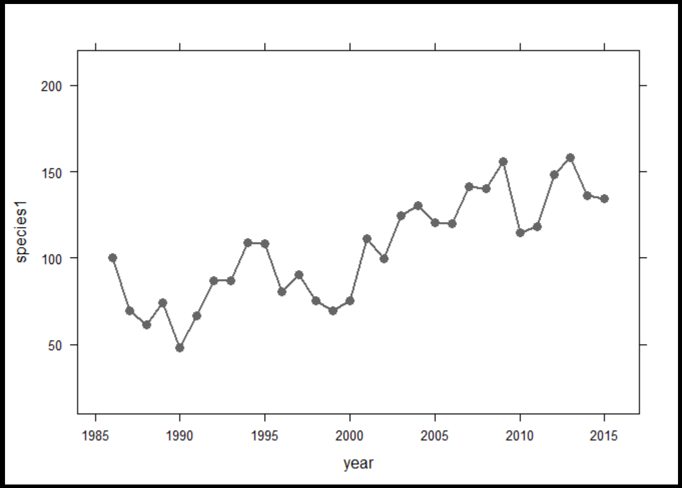

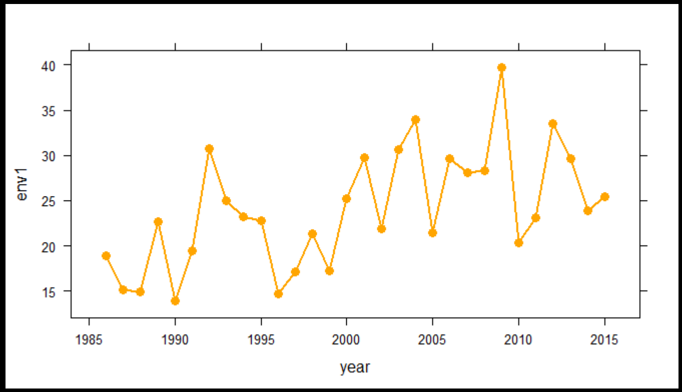

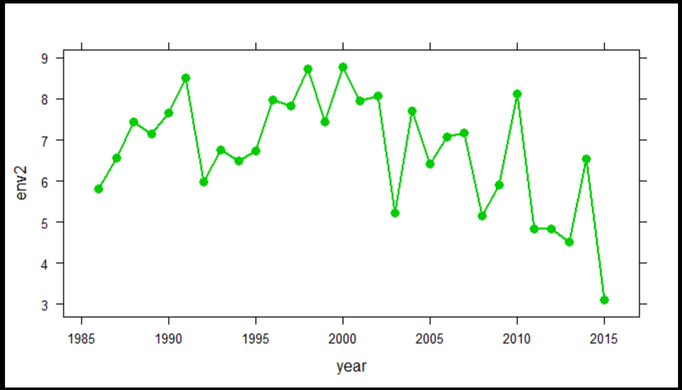

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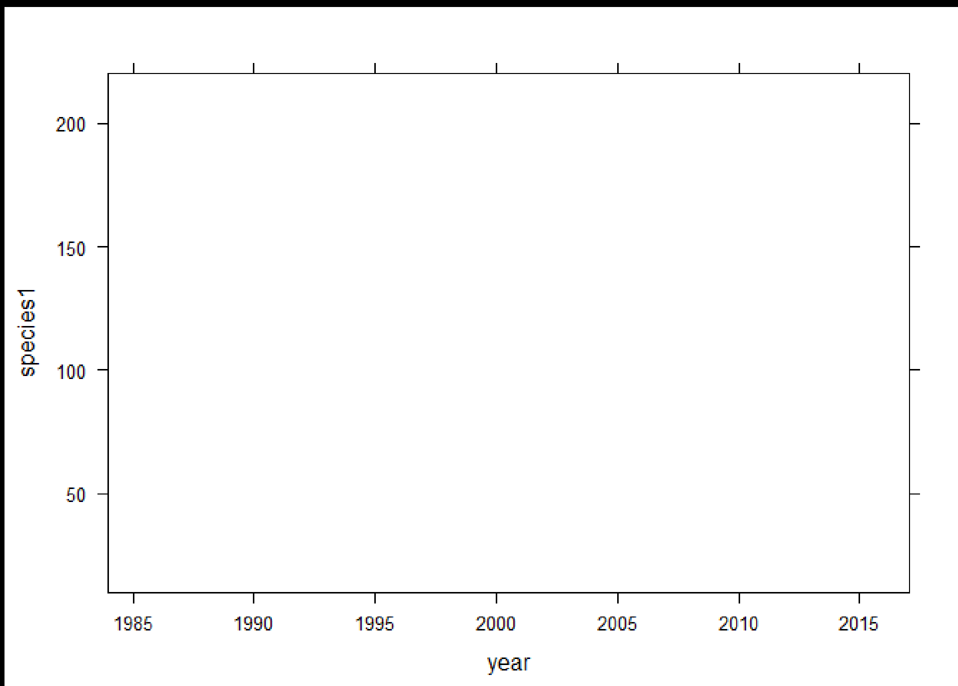

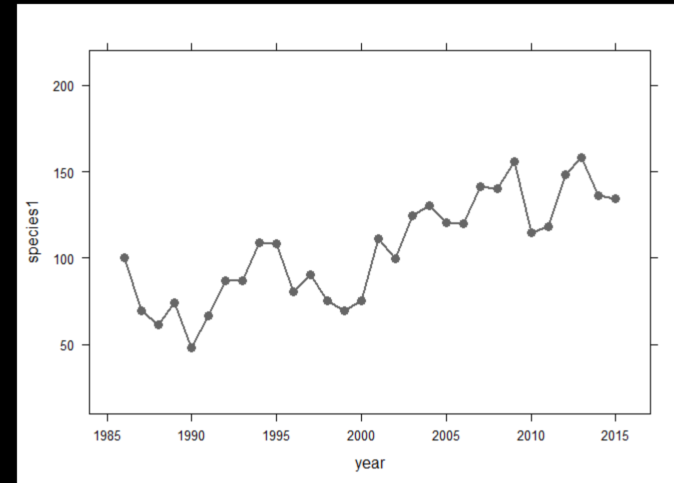

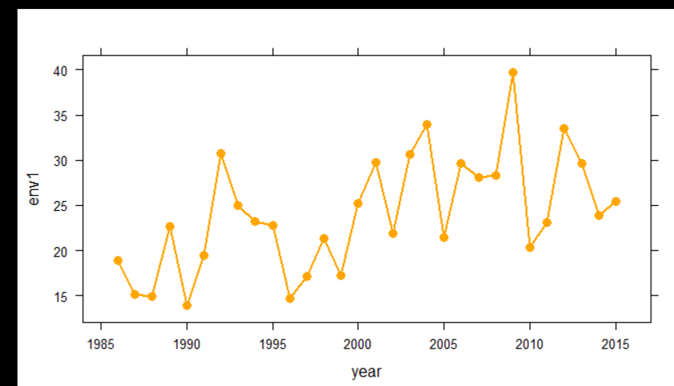

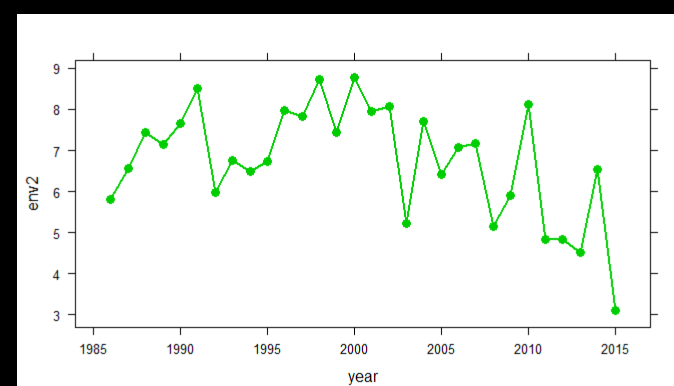

Sp1 estimate = $\text{Sp1}_{t\text{-}1}$ × 0.56 + Intercept 13.5 + Env1 × 2.4 + Env2 × -3.5

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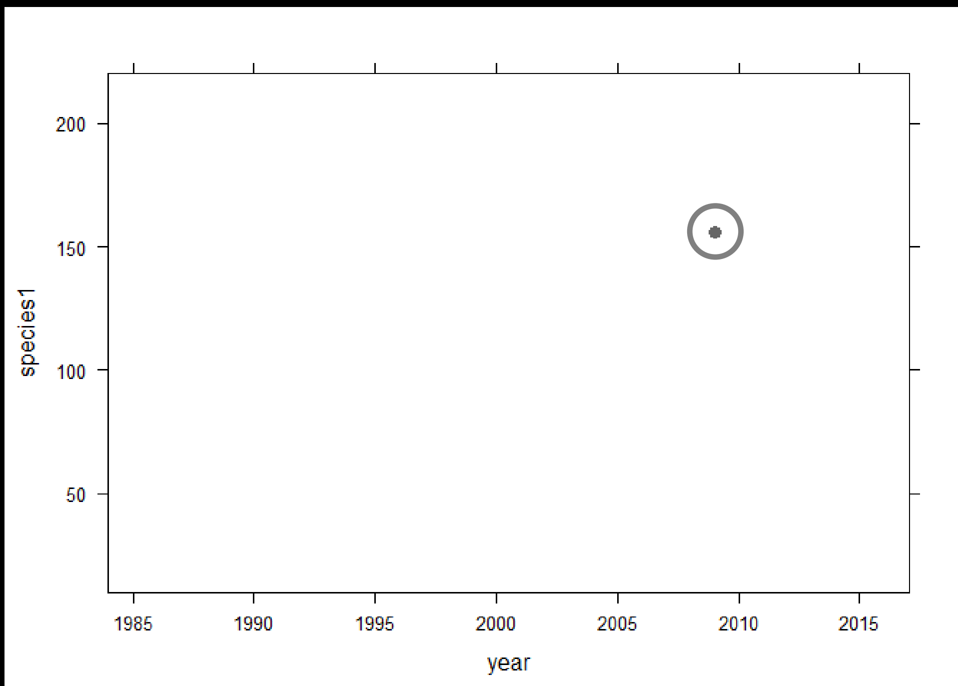

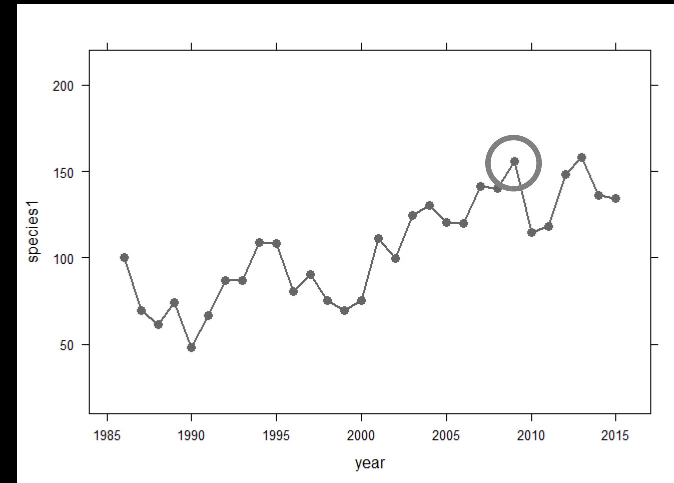

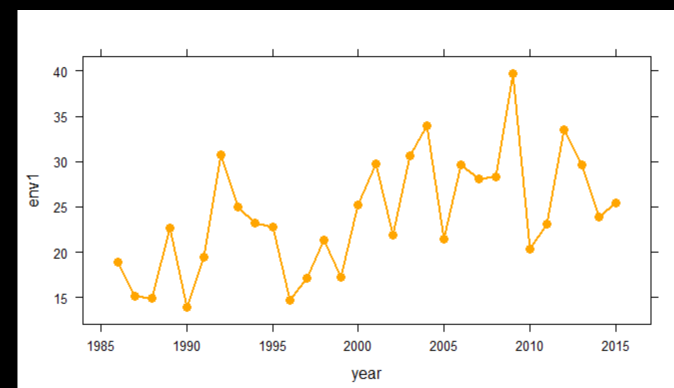

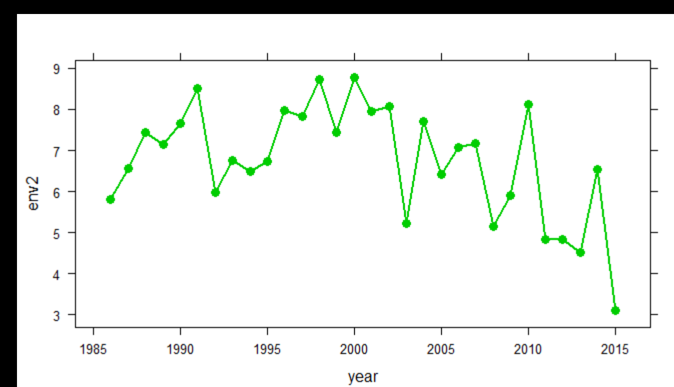

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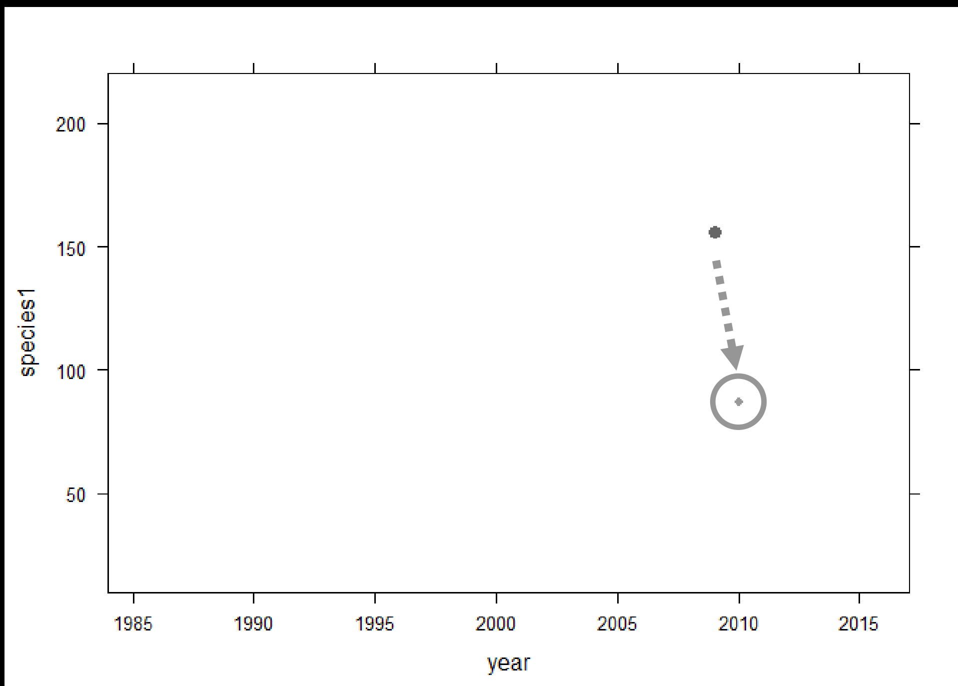

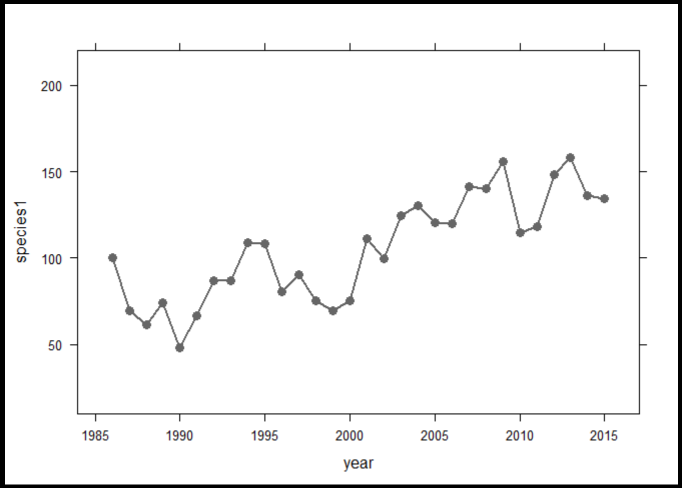

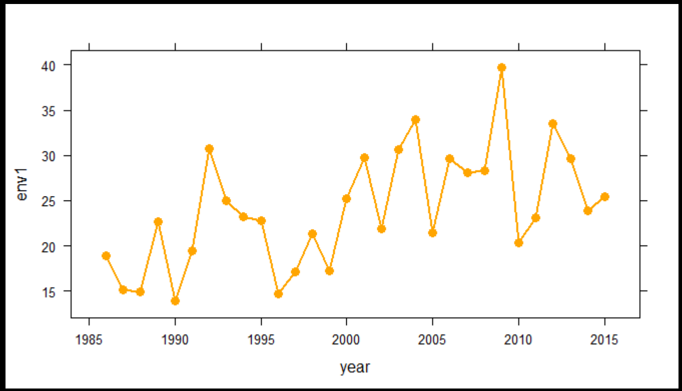

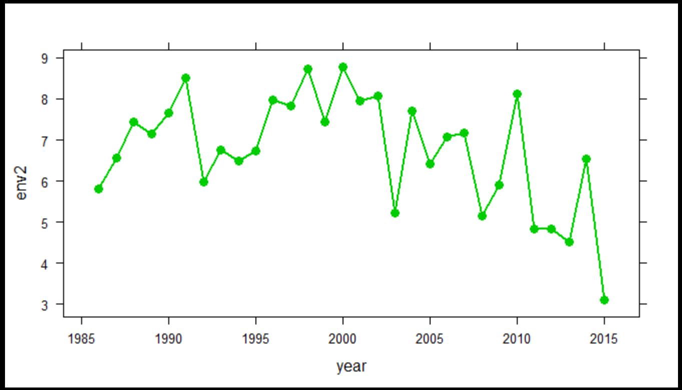

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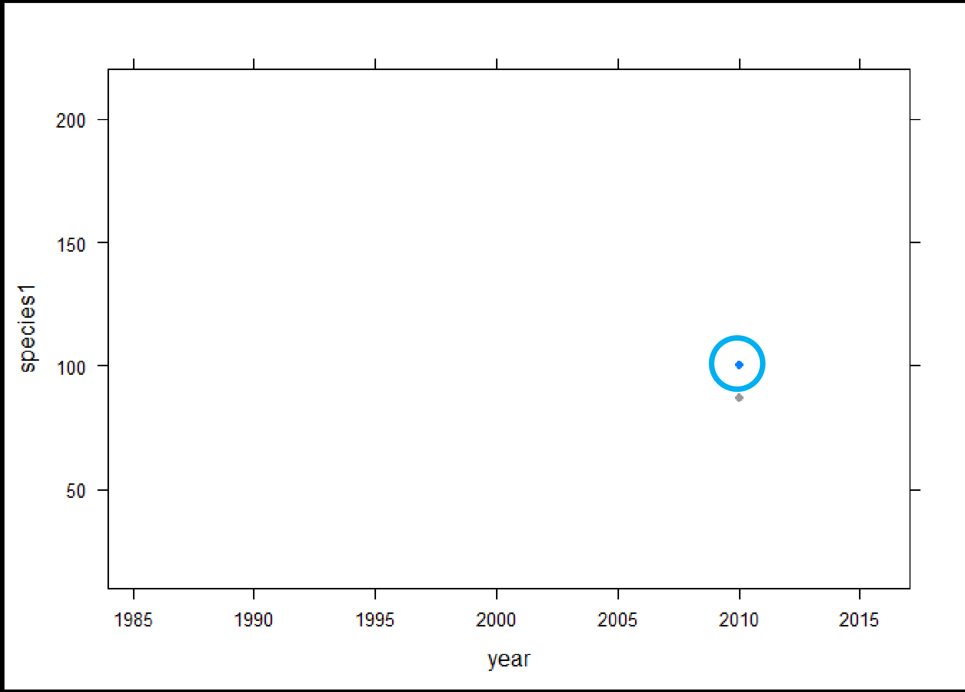

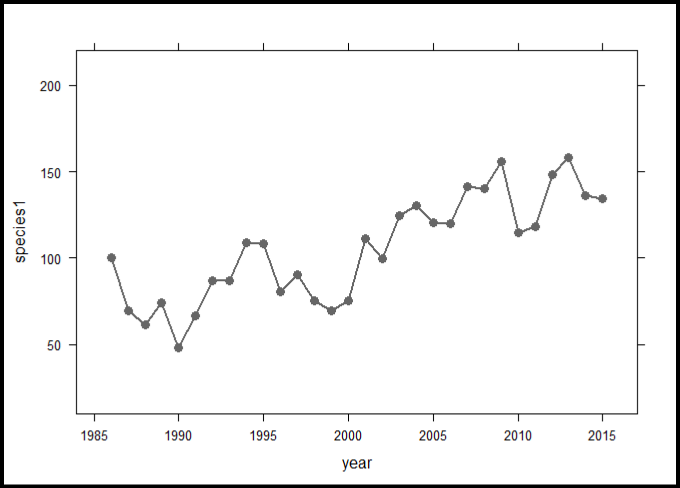

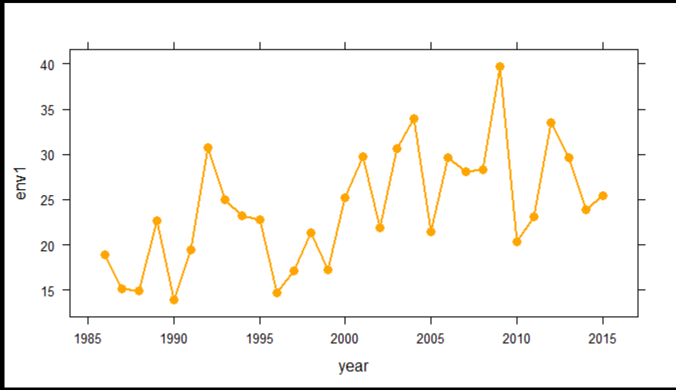

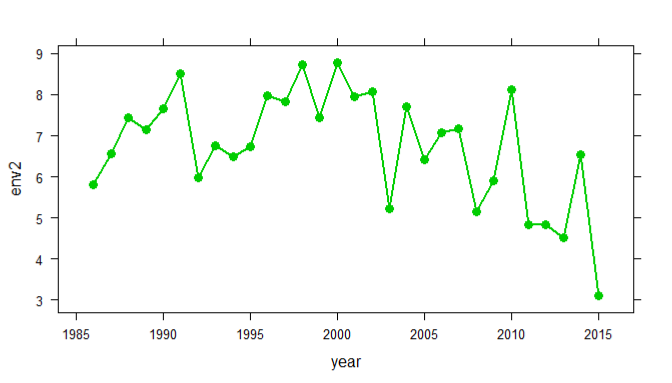

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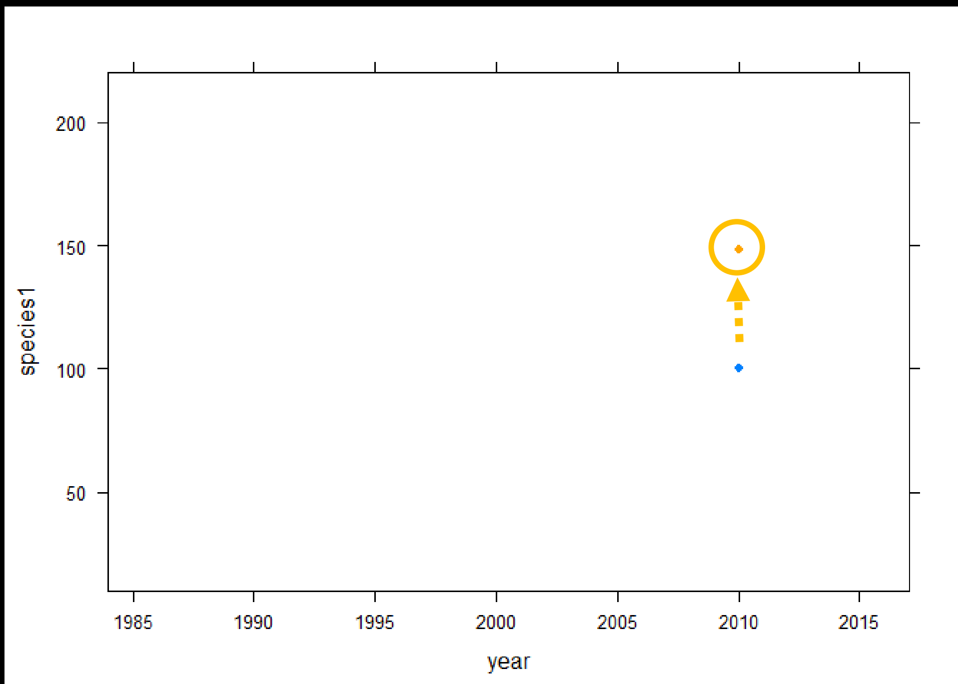

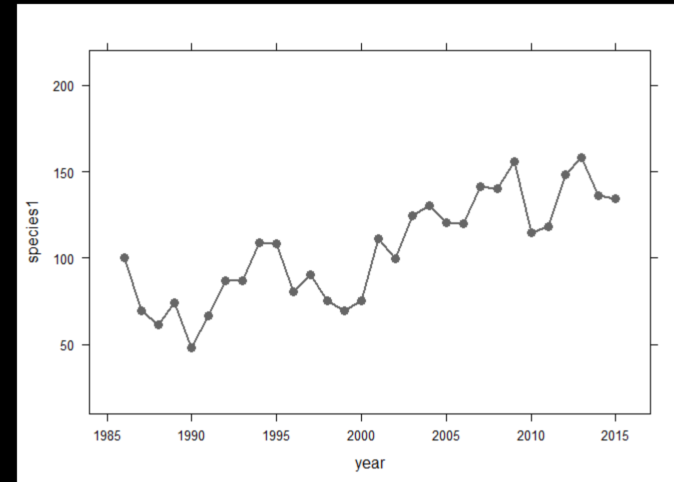

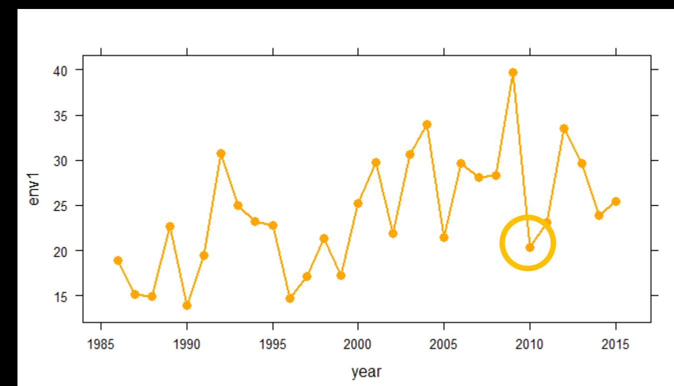

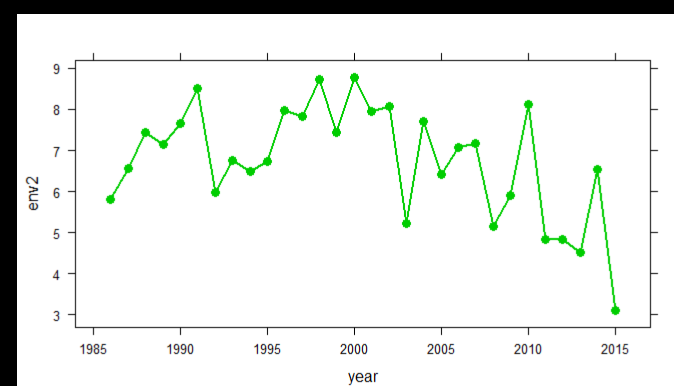

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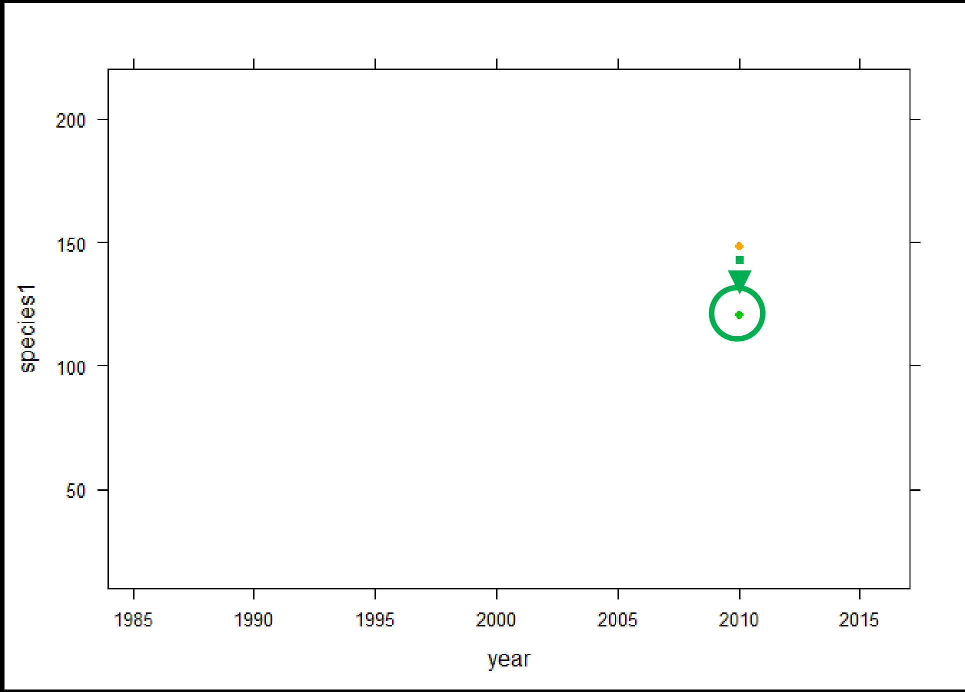

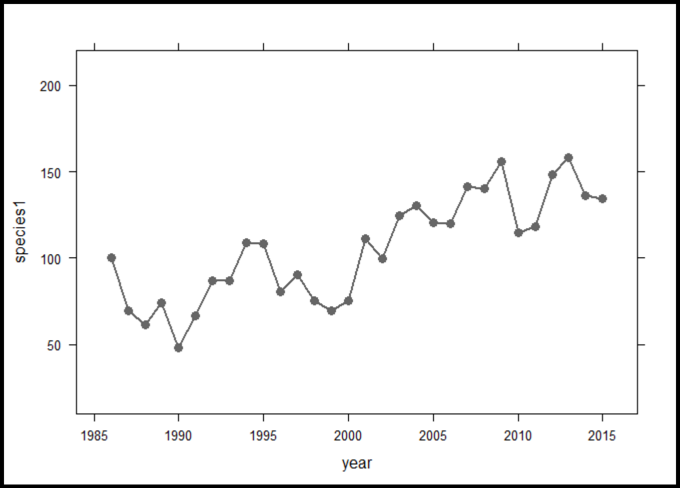

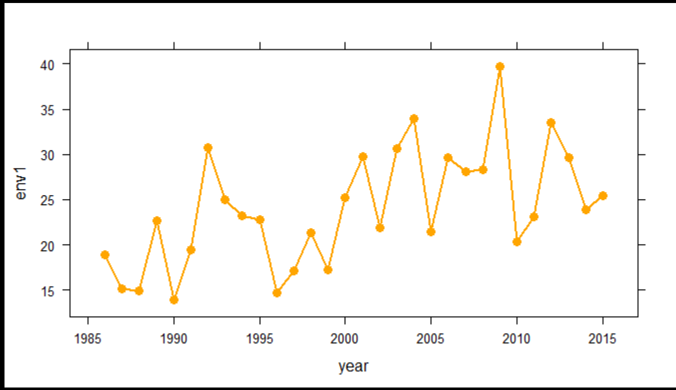

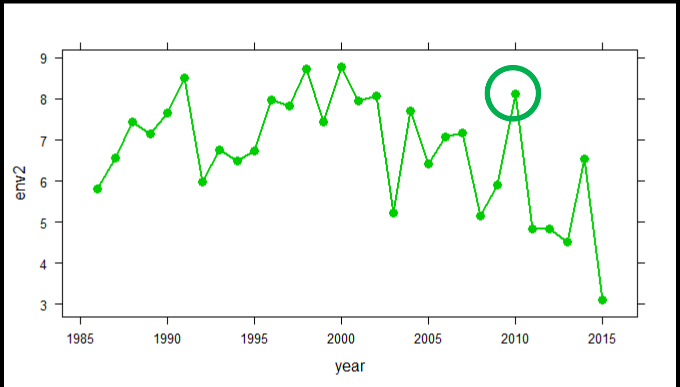

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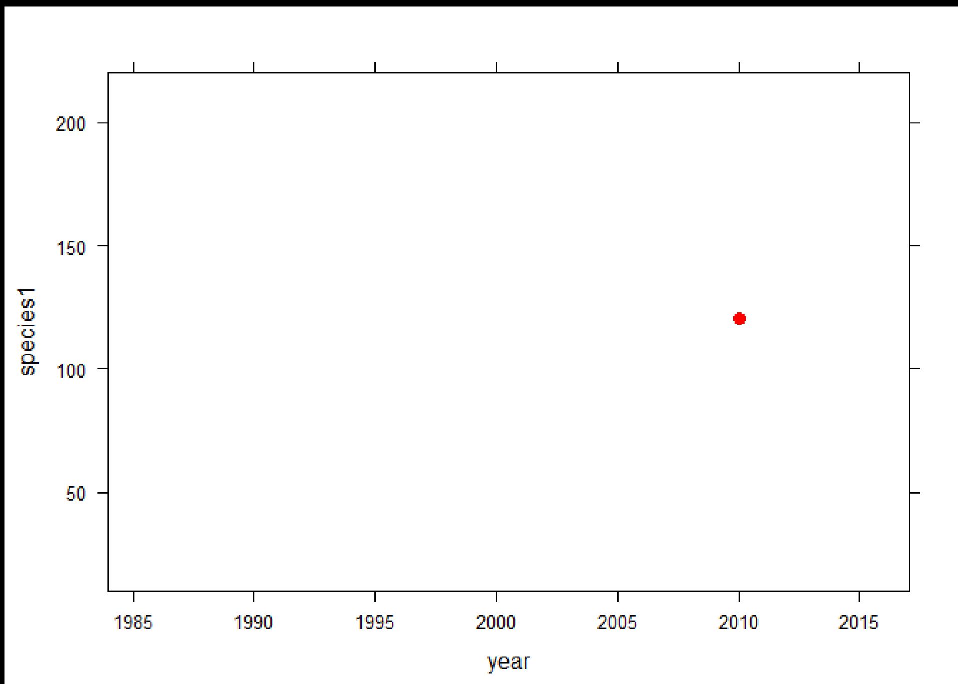

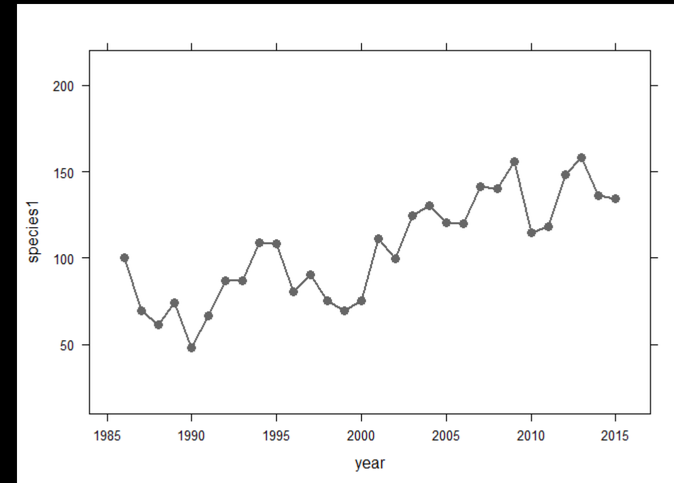

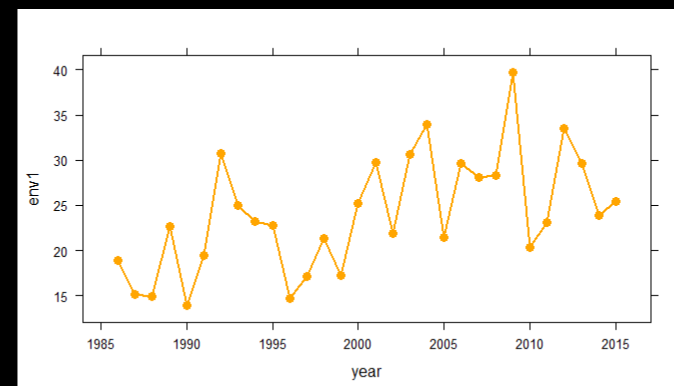

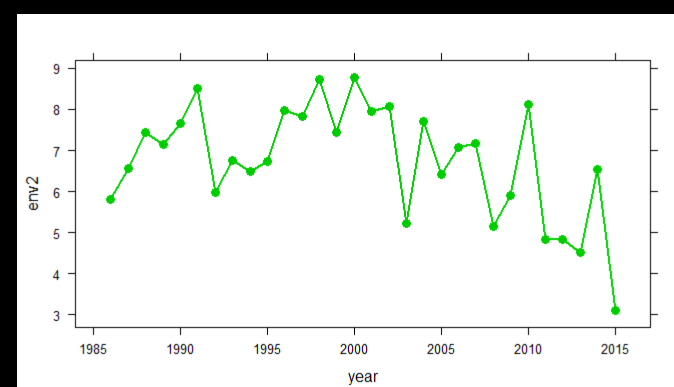

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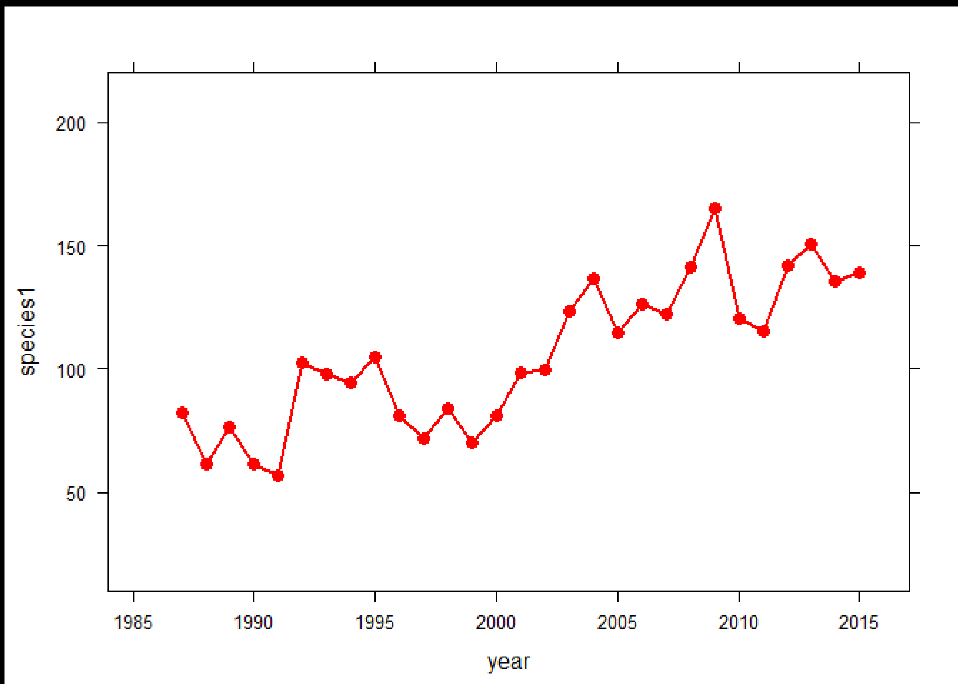

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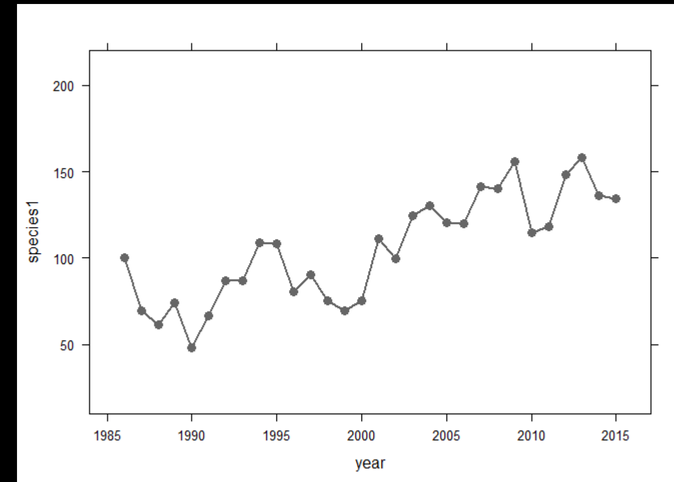
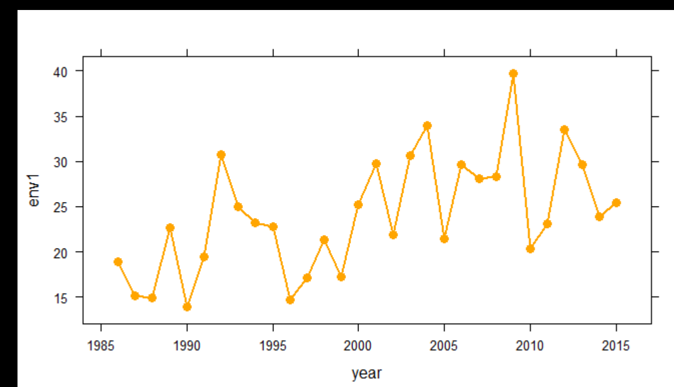
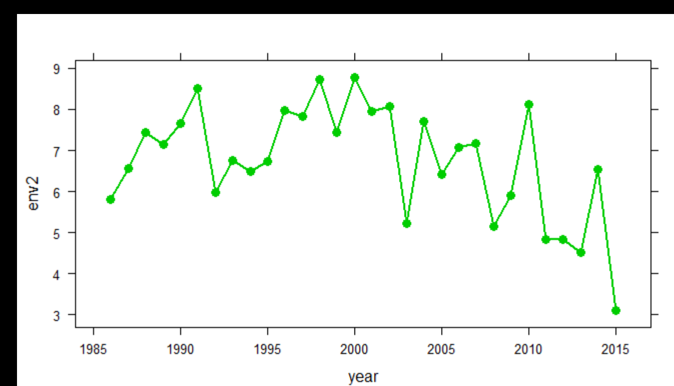
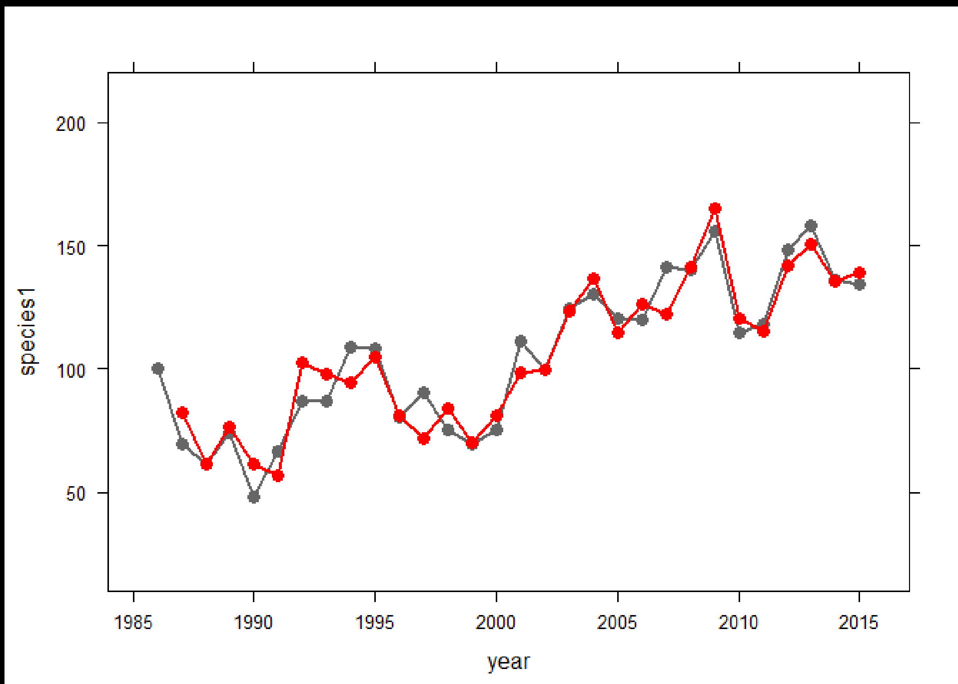


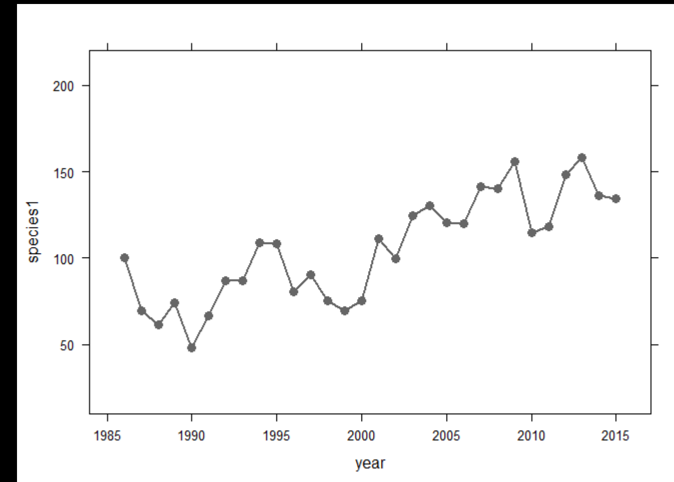


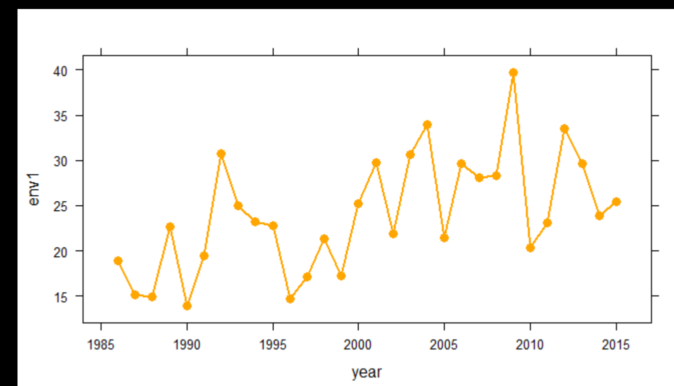


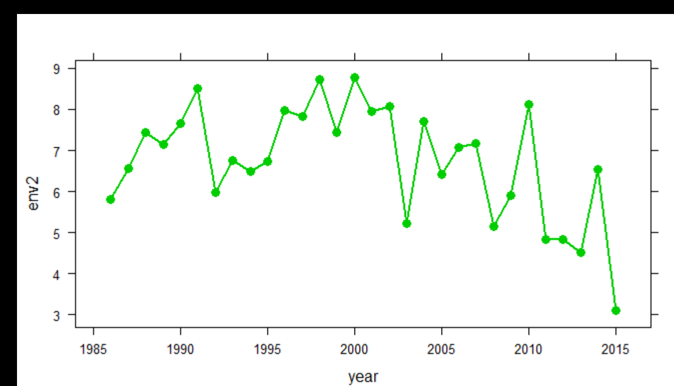
MAR models

Example: auto-regression





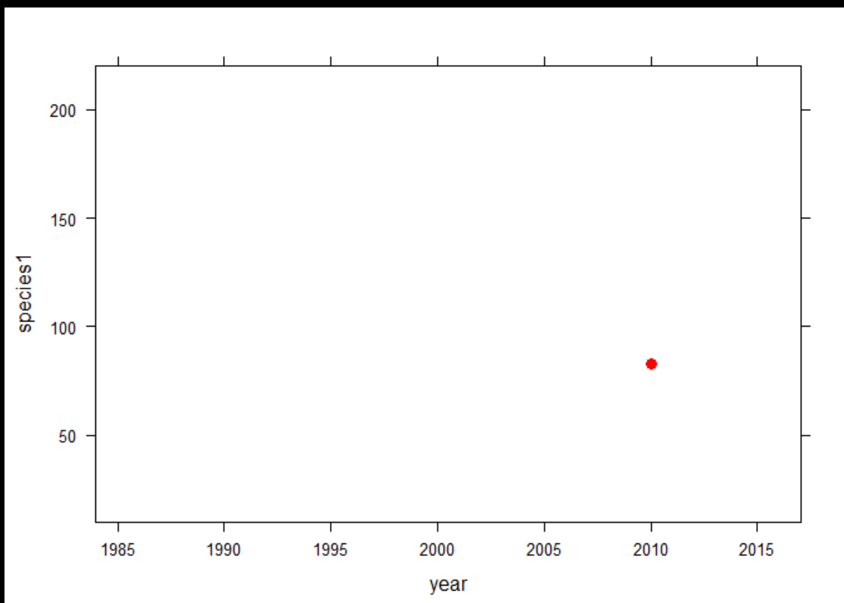




$$\text{Sp1 estimate} = \text{Sp1}_{t\text{-}1} \times 0.56 + \text{Intercept } 13.5 + \text{Env1} \times 2.4 + \text{Env2} \times \text{-}3.5$$

MAR models

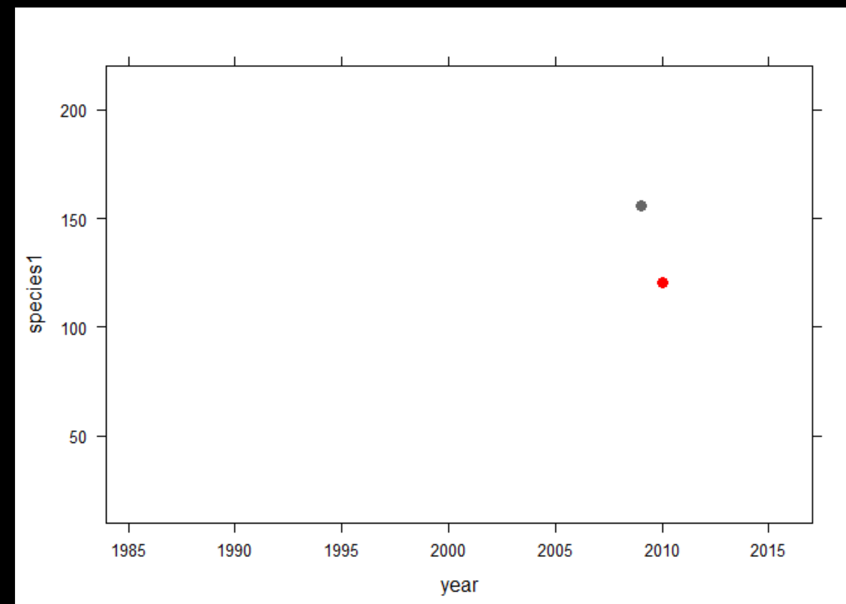
Example: no auto-regression



Sp1 estimate =

Intercept 90.6 + Env1 × 2.9 + Env2 × -8.2

Example: auto-regression

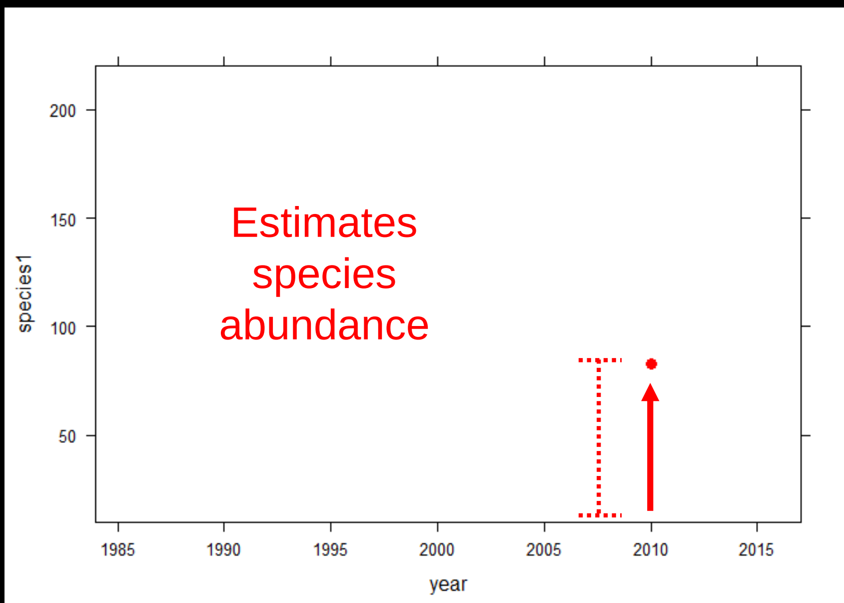


Sp1 estimate =

$Sp1_{t\text{-}1}$ × 0.56 + Intercept 13.5 + Env1 × 2.4 + Env2 × -3.5

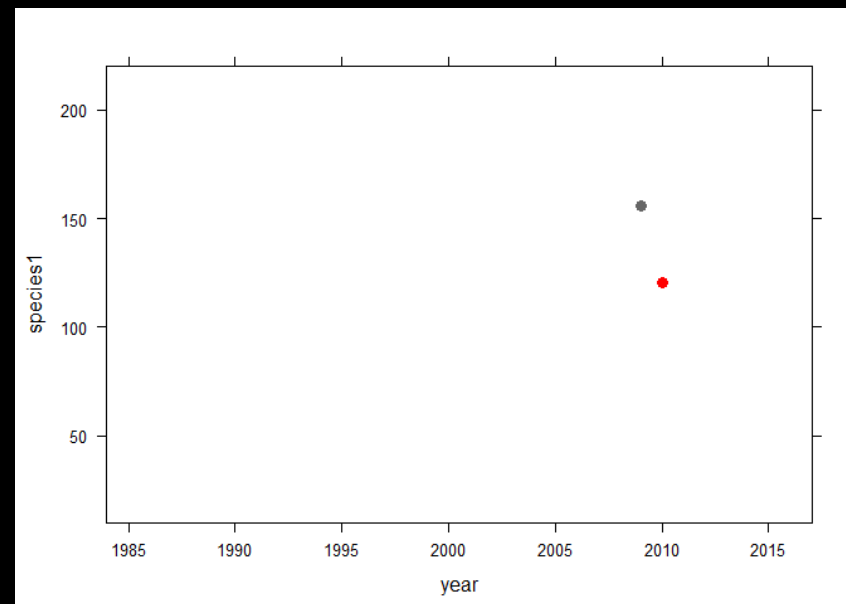
MAR models

Example: no auto-regression



Sp1 estimate = Intercept 90.6 + Env1 × 2.9 + Env2 × -8.2

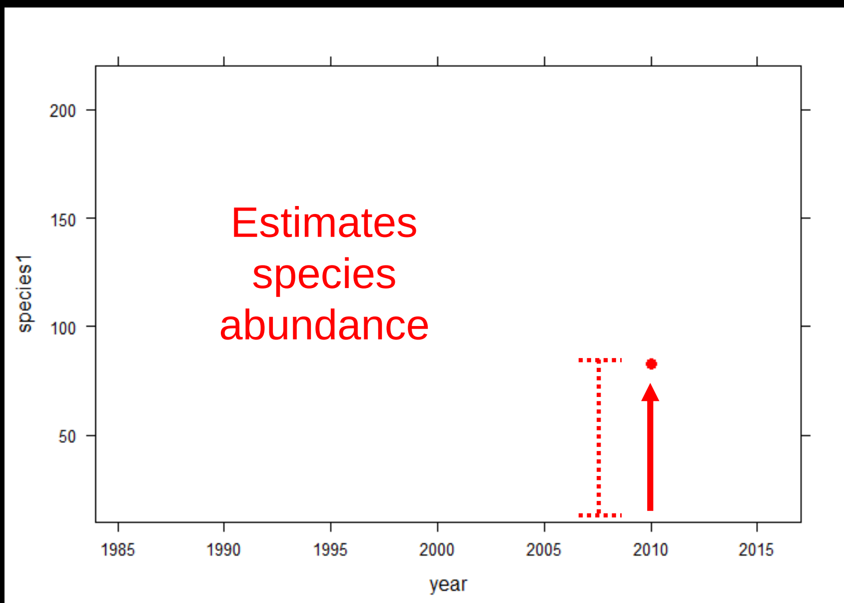
Example: auto-regression



Sp1 estimate = $Sp1_{t\text{-}1}$ × 0.56 + Intercept 13.5 + Env1 × 2.4 + Env2 × -3.5

MAR models

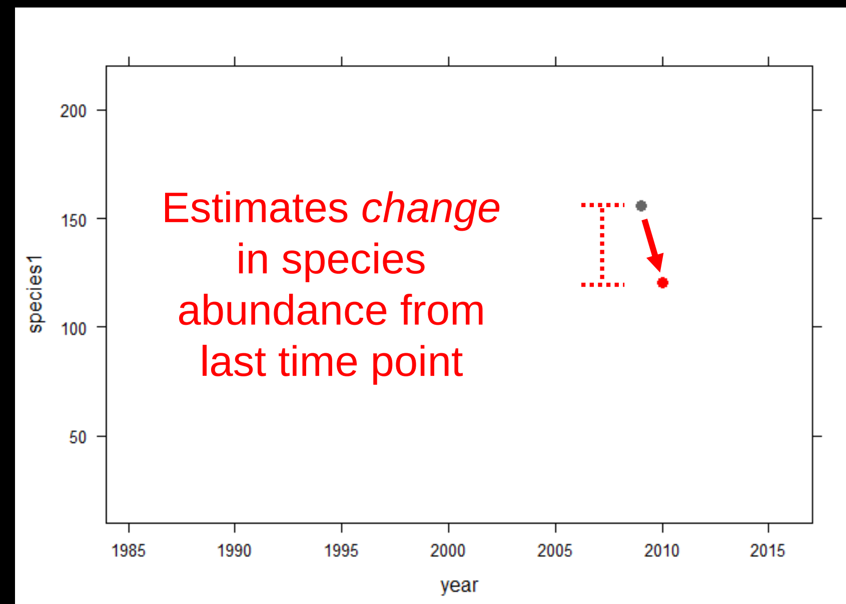
Example: no auto-regression



Sp1 estimate =

Intercept 90.6 + Env1 × 2.9 + Env2 × -8.2

Example: auto-regression



Sp1 estimate =

$Sp1_{t\text{-}1}$ × 0.56 + Intercept 13.5 + Env1 × 2.4 + Env2 × -3.5

MAR-1 models

$$\begin{matrix}\text{Sp1}_{t+1} \\ \text{estimate}\end{matrix} = \begin{matrix}\text{Intercept} \\ 0\end{matrix} + \begin{matrix}\underline{\text{Sp1}}_{t} \\ \times\ b_1\end{matrix} + \begin{matrix}\text{Sp2}_{t} \\ \times\ b_2\end{matrix} + \begin{matrix}\text{Sp3}_{t} \\ \times\ b_3\end{matrix} + \begin{matrix}\text{Env1}_{t} \\ \times\ c_1\end{matrix} + \begin{matrix}\text{Env2}_{t} \\ \times\ c_2\end{matrix}$$

MAR-1 models

$$\underset{\text{estimate}}{Sp1_{t+1}} = \underset{0}{\text{Intercept}} + \underbrace{\underline{Sp1}_{t} \times b_1 + Sp2_{t} \times b_2 + Sp3_{t} \times b_3 + Env1_{t} \times c_1 + Env2_{t} \times c_2}$$

MAR-1 models

$$\underset{\text{estimate}}{\mathrm{Sp1}_{t+1}} = \underset{0}{\text{Intercept}} + \mathrm{Sp1}_t \times \mathbf{b_1} + \mathrm{Sp2}_t \times \mathbf{b_2} + \mathrm{Sp3}_t \times \mathbf{b_3} + \mathrm{Env1}_t \times \mathbf{c_1} + \mathrm{Env2}_t \times \mathbf{c_2}$$

MAR-1 models

$$\underset{\text{estimate}}{Sp1_{t+1}} = \underset{0}{\text{Intercept}} + Sp1_t \times \mathbf{b_1} + Sp2_t \times \mathbf{b_2} + Sp3_t \times \mathbf{b_3} + Env1_t \times \mathbf{c_1} + Env2_t \times \mathbf{c_2}$$

	Sp1	Sp2	Sp3	Env1	Env2
Sp1					

MAR-1 models

$$\underset{\text{estimate}}{\mathrm{Sp1}_{t+1}} = \underset{0}{\text{Intercept}} + \mathrm{Sp1}_t \times \mathbf{b_1} + \mathrm{Sp2}_t \times \mathbf{b_2} + \mathrm{Sp3}_t \times \mathbf{b_3} + \mathrm{Env1}_t \times \mathbf{c_1} + \mathrm{Env2}_t \times \mathbf{c_2}$$

	Sp1	Sp2	Sp3	Env1	Env2
Sp1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$c_{1,1}$	$c_{1,2}$

MAR-1 models

$$\text{Sp1}_{t+1}\ \text{estimate} = \text{Intercept } 0 + \text{Sp1}_t \times b_1 + \text{Sp2}_t \times b_2 + \text{Sp3}_t \times b_3 + \text{Env1}_t \times c_1 + \text{Env2}_t \times c_2$$

$$\text{Sp2}_{t+1}\ \text{estimate} = \text{Intercept } 0 + \text{Sp1}_t \times b_1 + \text{Sp2}_t \times b_2 + \text{Sp3}_t \times b_3 + \text{Env1}_t \times c_1 + \text{Env2}_t \times c_2$$

	Sp1	Sp2	Sp3	Env1	Env2
Sp1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$c_{1,1}$	$c_{1,2}$
Sp2	$b_{2,1}$	$b_{2,2}$	$b_{2,3}$	$c_{2,1}$	$c_{2,2}$

MAR-1 models

$$\text{Sp1}_{t+1}\ \text{estimate} = \text{Intercept}\ 0 + \text{Sp1}_t \times b_1 + \text{Sp2}_t \times b_2 + \text{Sp3}_t \times b_3 + \text{Env1}_t \times c_1 + \text{Env2}_t \times c_2$$

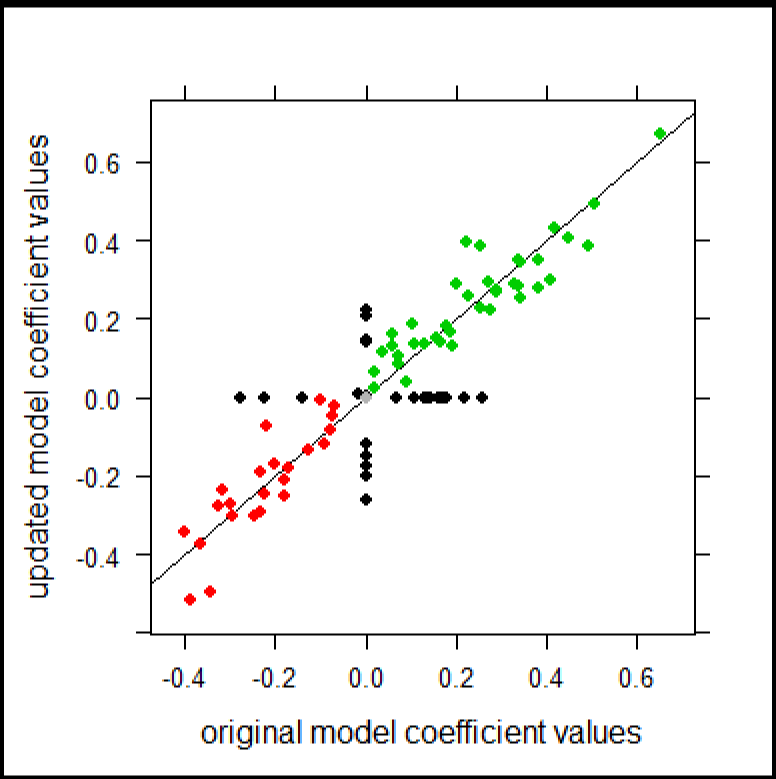
$$\text{Sp2}_{t+1}\ \text{estimate} = \text{Intercept}\ 0 + \text{Sp1}_t \times b_1 + \text{Sp2}_t \times b_2 + \text{Sp3}_t \times b_3 + \text{Env1}_t \times c_1 + \text{Env2}_t \times c_2$$

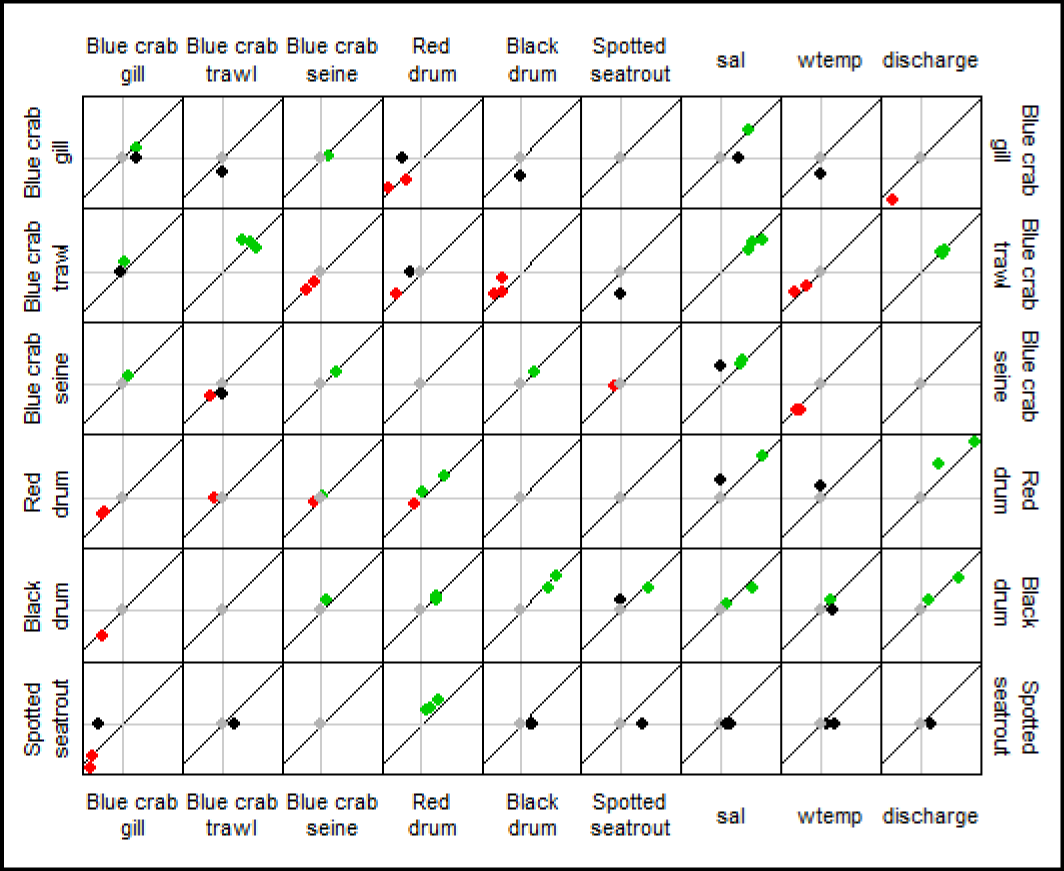
$$\text{Sp3}_{t+1}\ \text{estimate} = \text{Intercept}\ 0 + \text{Sp1}_t \times b_1 + \text{Sp2}_t \times b_2 + \text{Sp3}_t \times b_3 + \text{Env1}_t \times c_1 + \text{Env2}_t \times c_2$$

	Sp1	Sp2	Sp3	…	Env1	Env2	…
Sp1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	…	$c_{1,1}$	$c_{1,2}$	…
Sp2	$b_{2,1}$	$b_{2,2}$	$b_{2,3}$	…	$c_{2,1}$	$c_{2,2}$	…
Sp3	$b_{3,1}$	$b_{3,2}$	$b_{3,3}$	…	$c_{3,1}$	$c_{3,2}$	…
…	…	…	…	…	…	…	…

Updated vs. Original Data Models

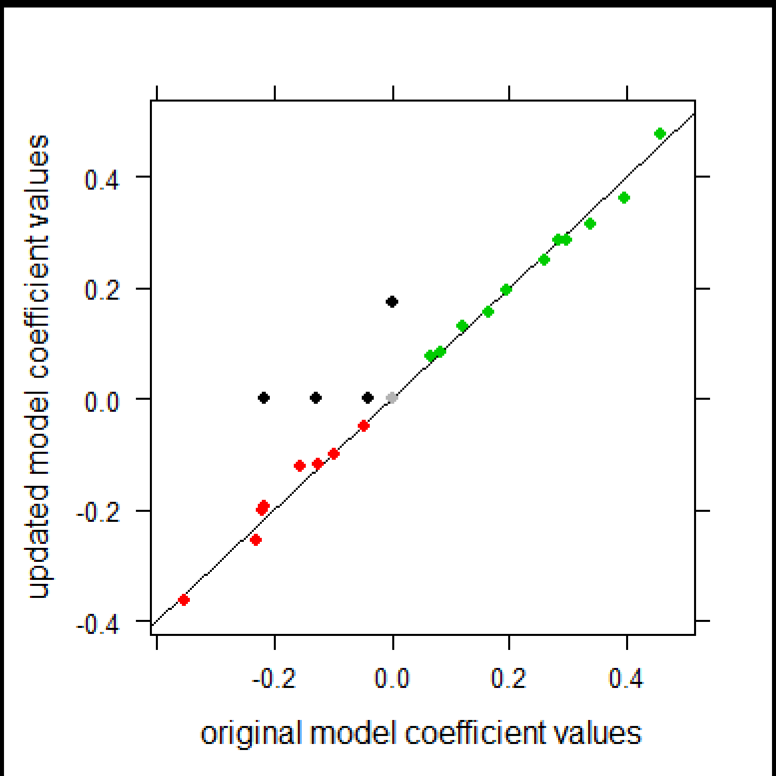
Blue crab 2-year lag
Coefficient values

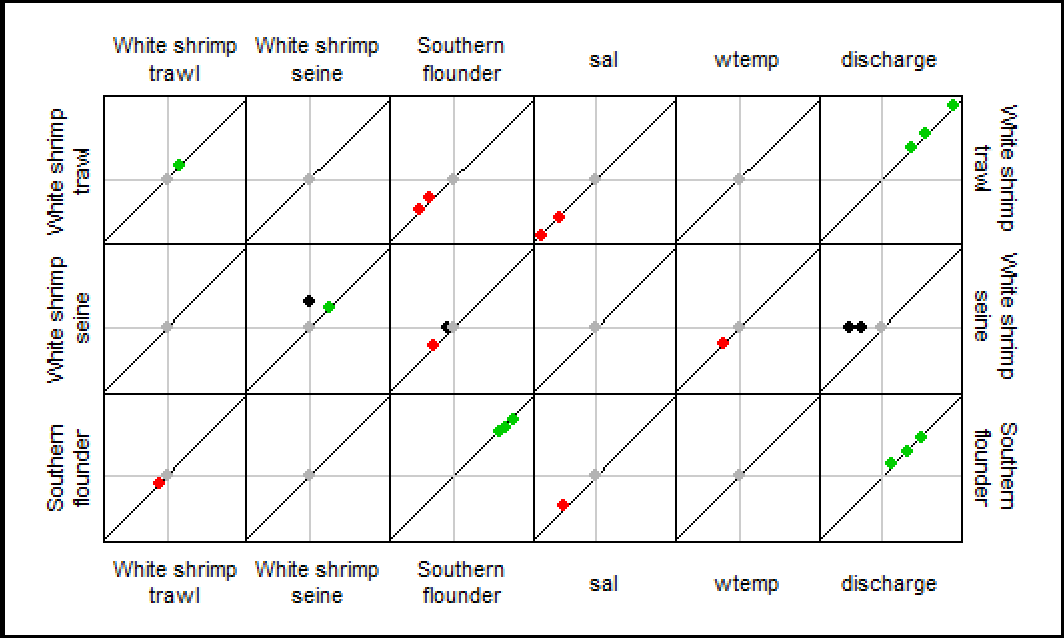




Updated vs. Original Data Models

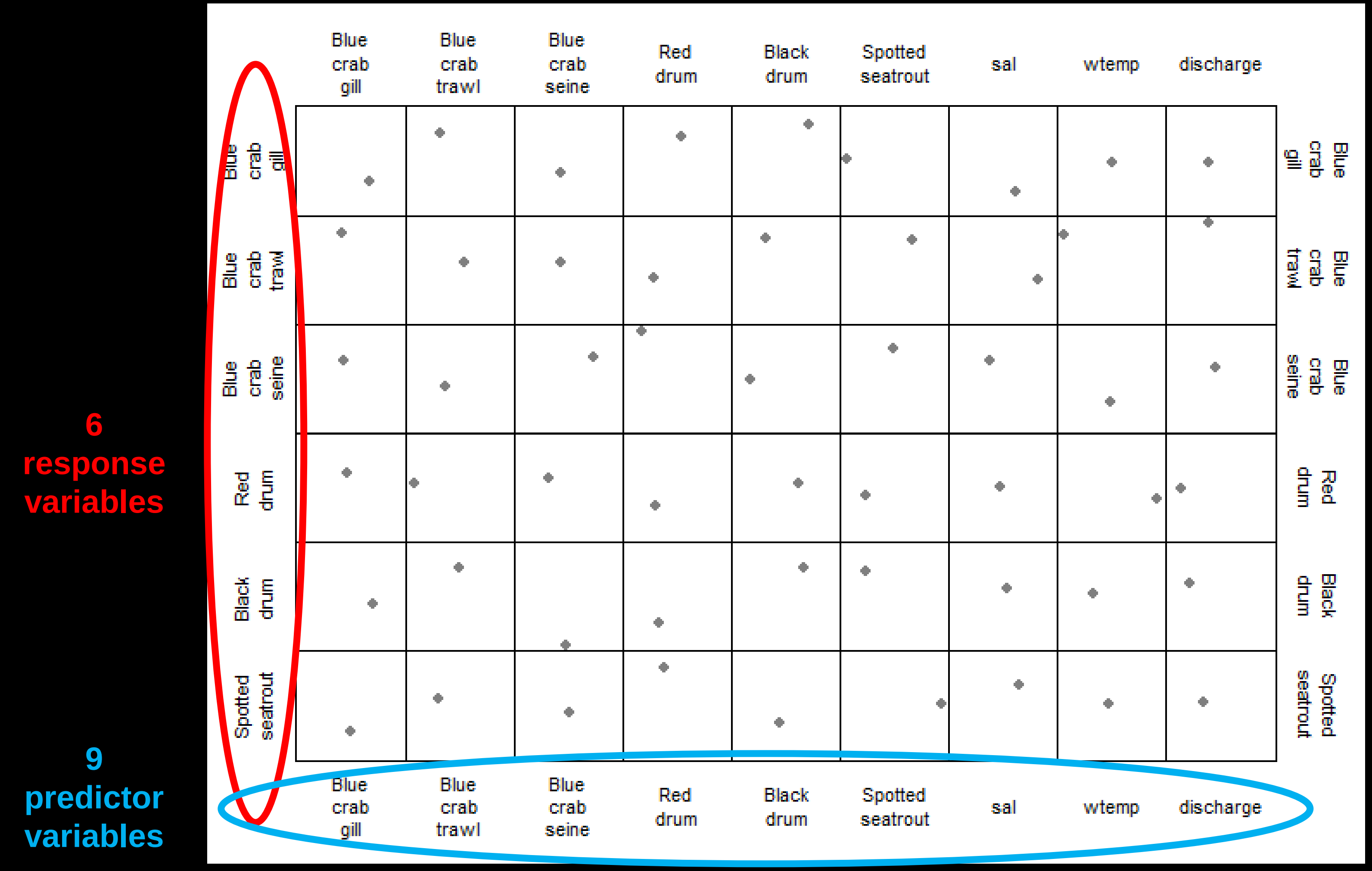
White shrimp 6-month lag
Coefficient values





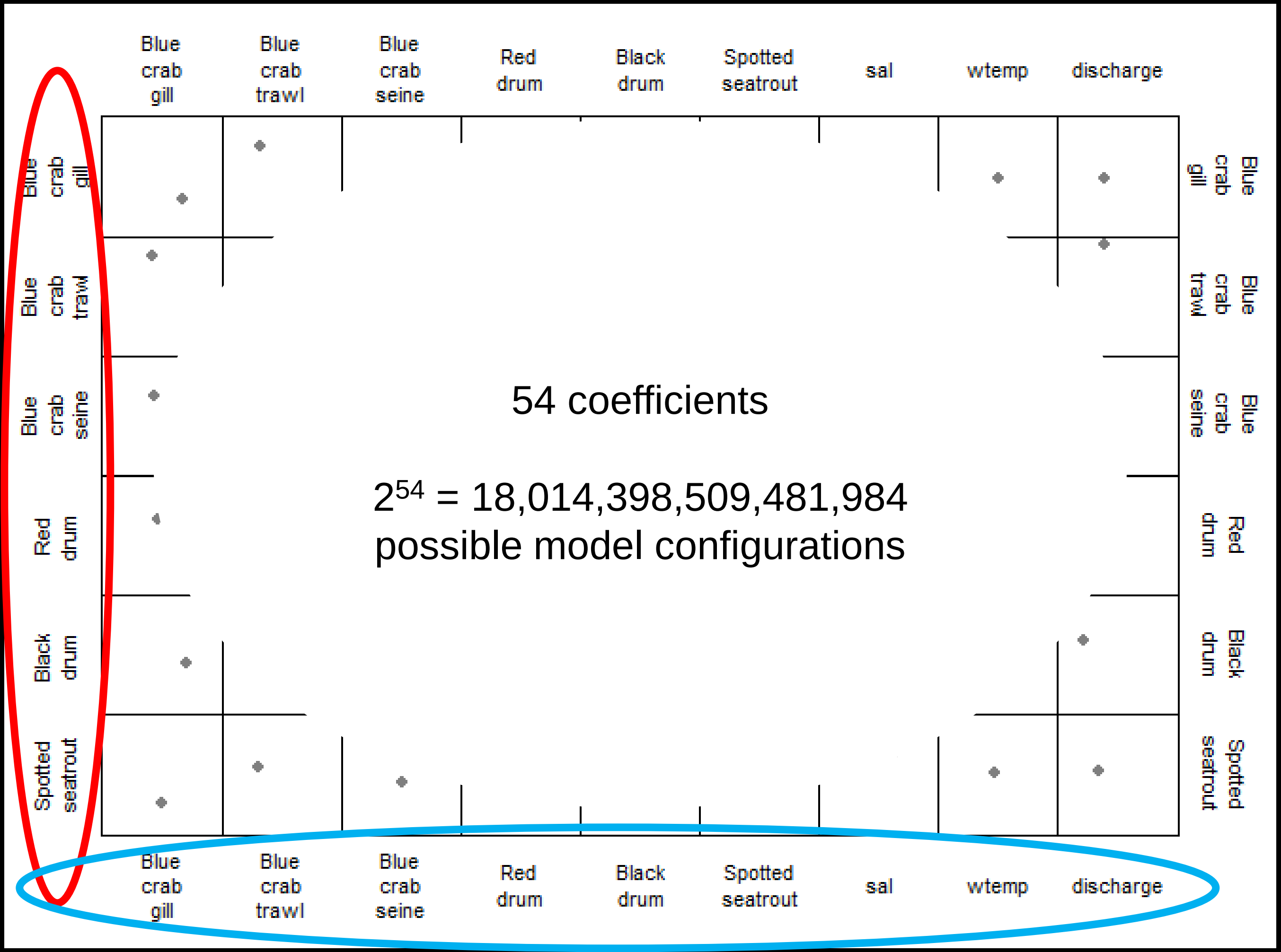
Seasonal models

Blue crab: original model



Seasonal models

Blue crab: original model



54 coefficients

2^{54} = 18,014,398,509,481,984 possible model configurations

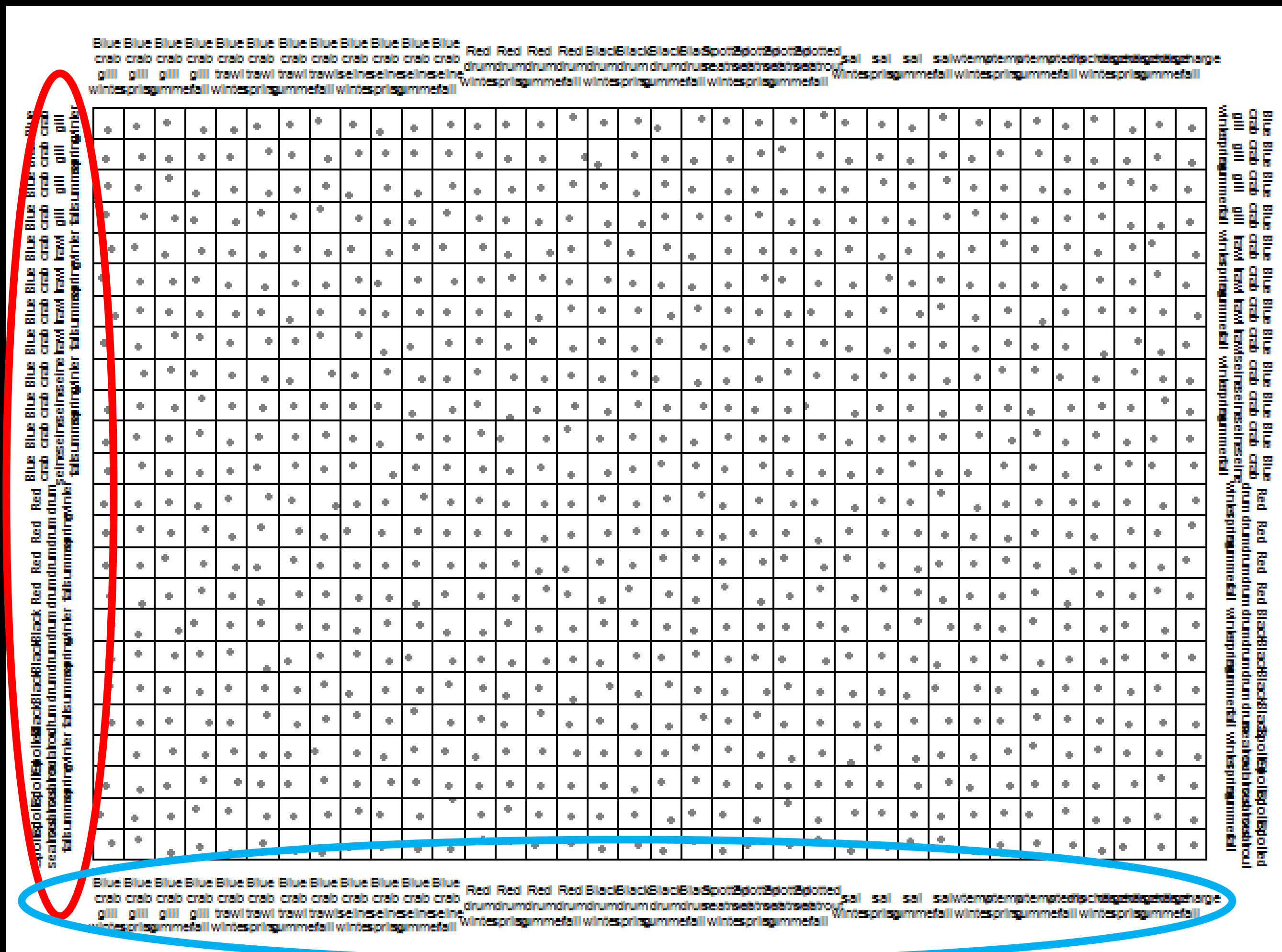
6 response variables

9 predictor variables

Seasonal models

Blue crab: Model with 4 seasons included

6 × 4 = 24 response variables

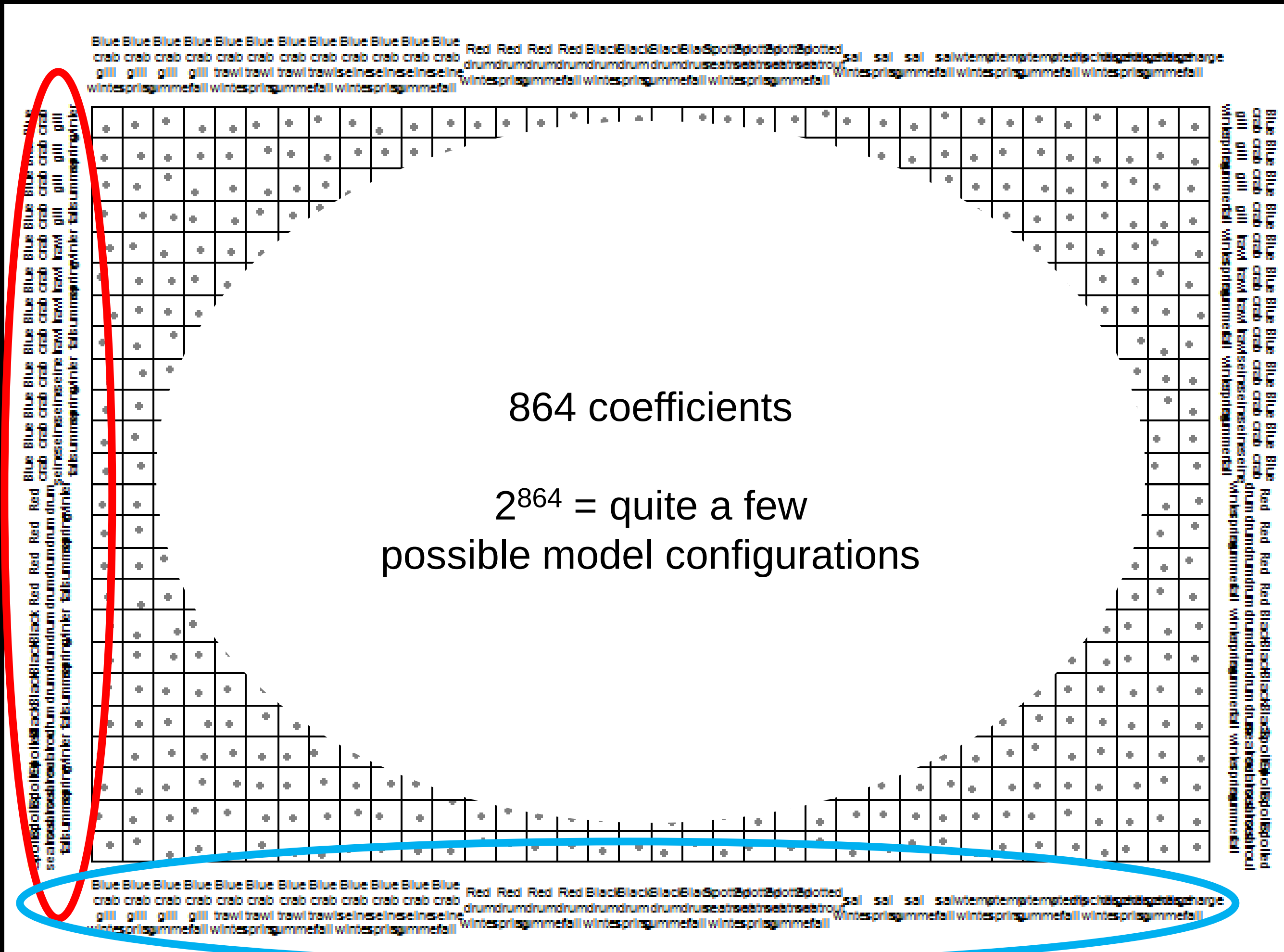


9 × 4 = 36 predictor variables

Seasonal models

Blue crab: Model with 4 seasons included

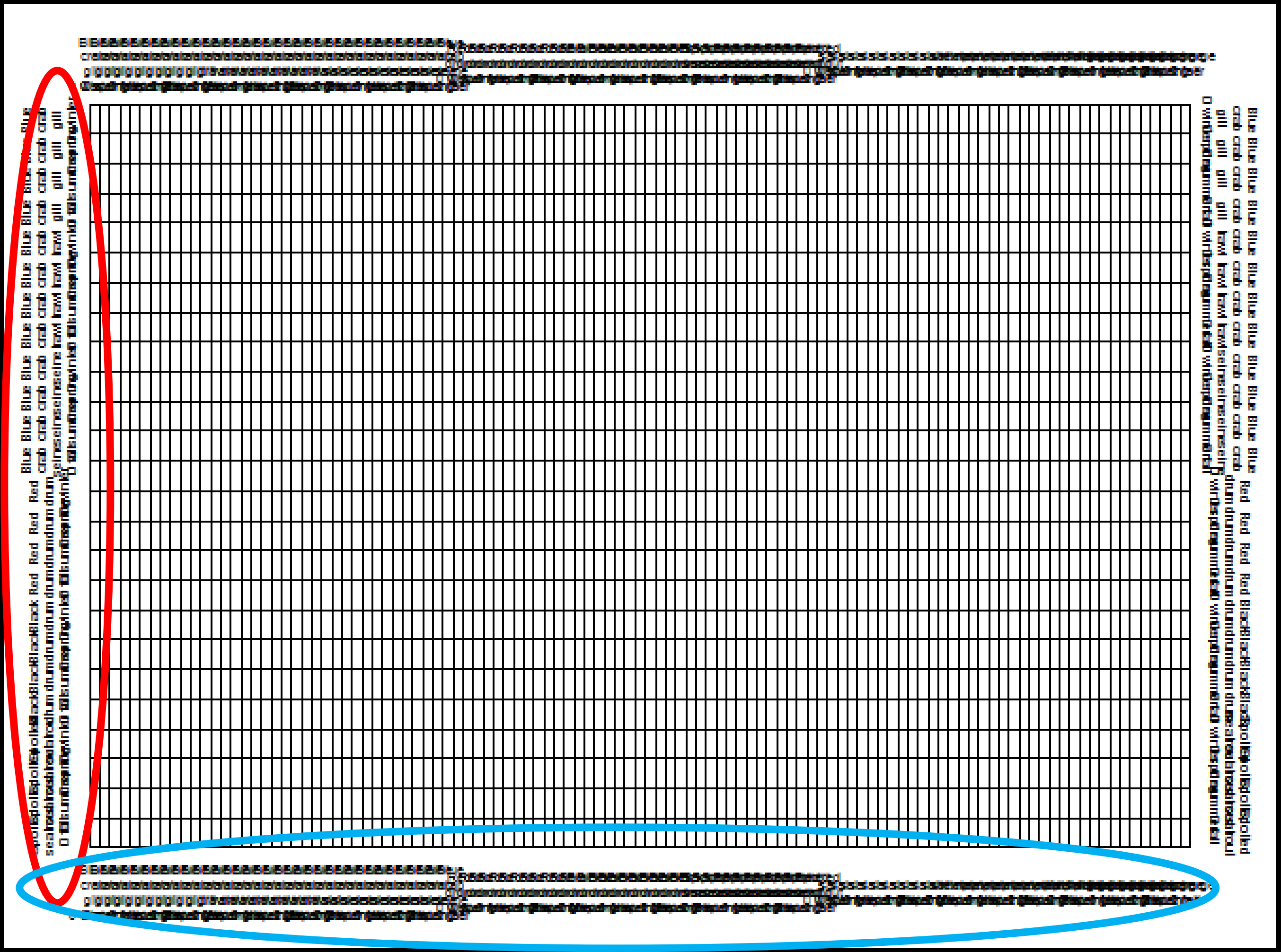
6 × 4 = 24 response variables



9 × 4 = 36 predictor variables

Seasonal models

Blue crab: Model with 4 seasons & 2 year lags included

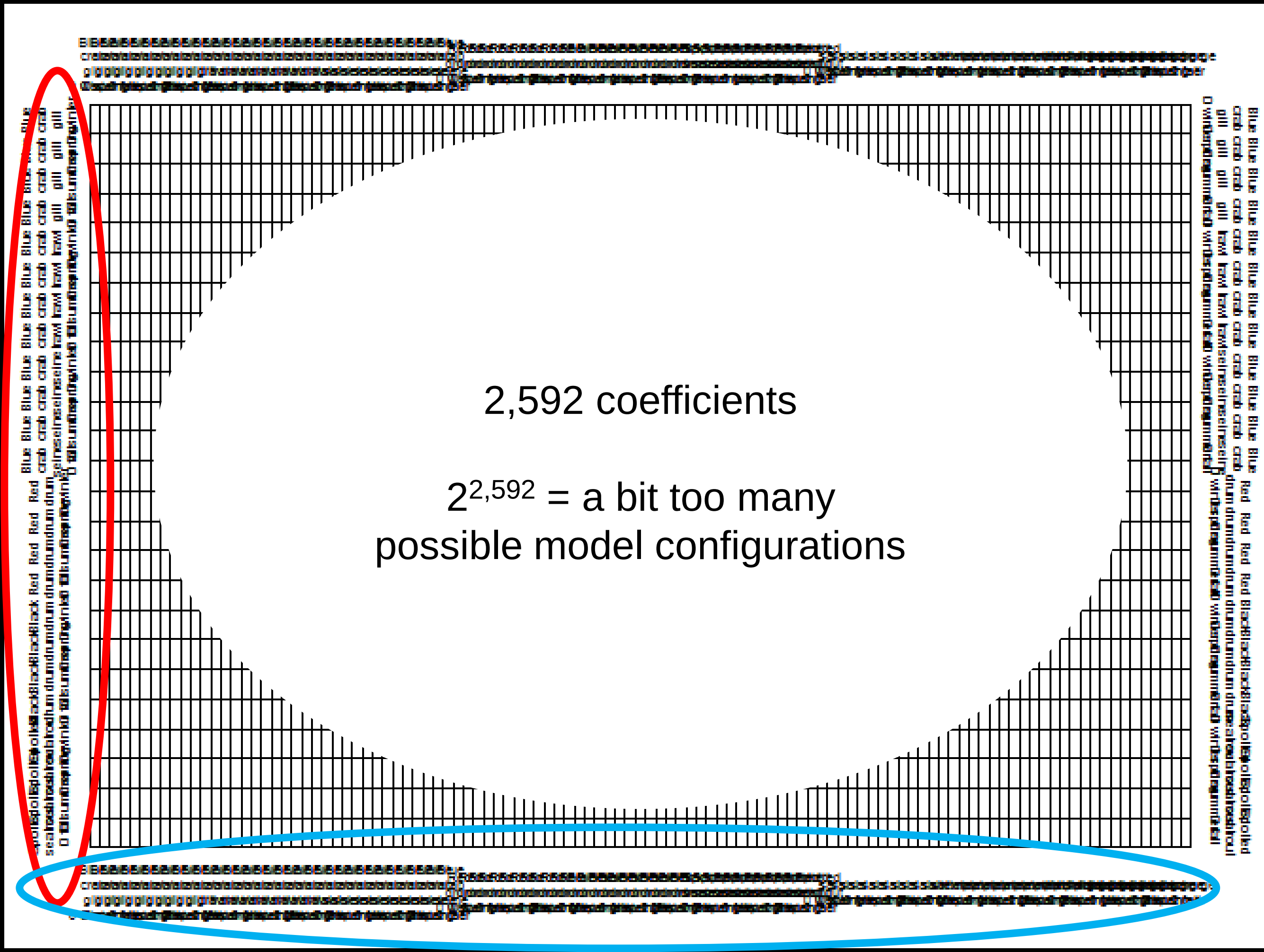


24 response variables

36 × 3 = 108 predictor variables

Seasonal models

Blue crab: Model with 4 seasons & 2 year lags included



24 response variables

36 × 3 = 108 predictor variables

Seasonal models

Models with 4 seasons & up to 2 year lags included

Seasonal models

Models with 4 seasons & up to 2 year lags included

- Focus on trawl datasets for focal species responses
  - Trawl samples taken throughout bays rather than only along perimeters (gill net and seine samples)
  - Trawl samples taken year-round rather than only in spring and fall (gill net samples)
  - Most consistent and ecologically plausible results in original models

Seasonal models

Models with 4 seasons & up to 2 year lags included

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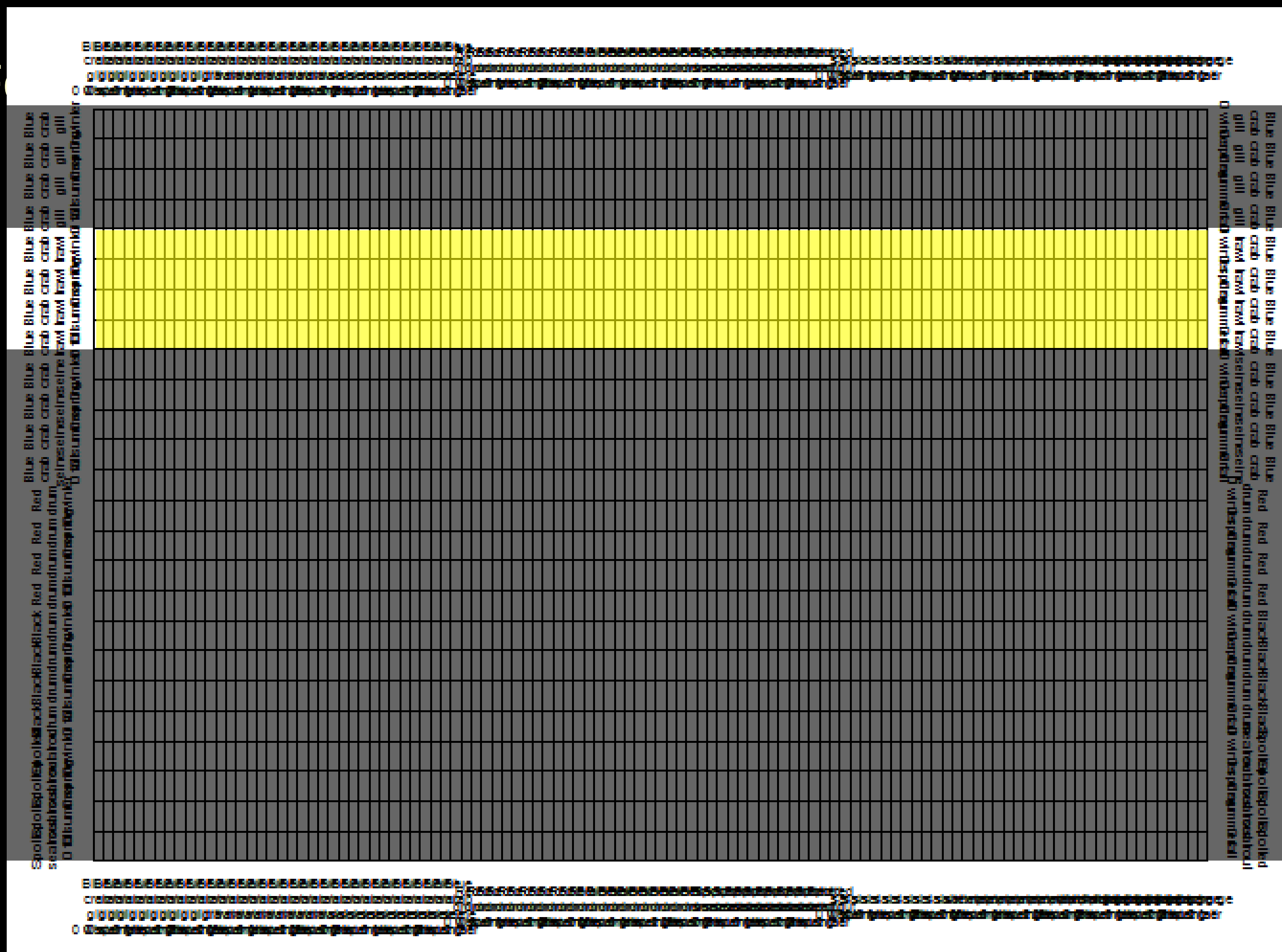

Seasonal models

Models with 4 seasons & up to 2 year lags included

- Focus on trawl datasets for focal species responses
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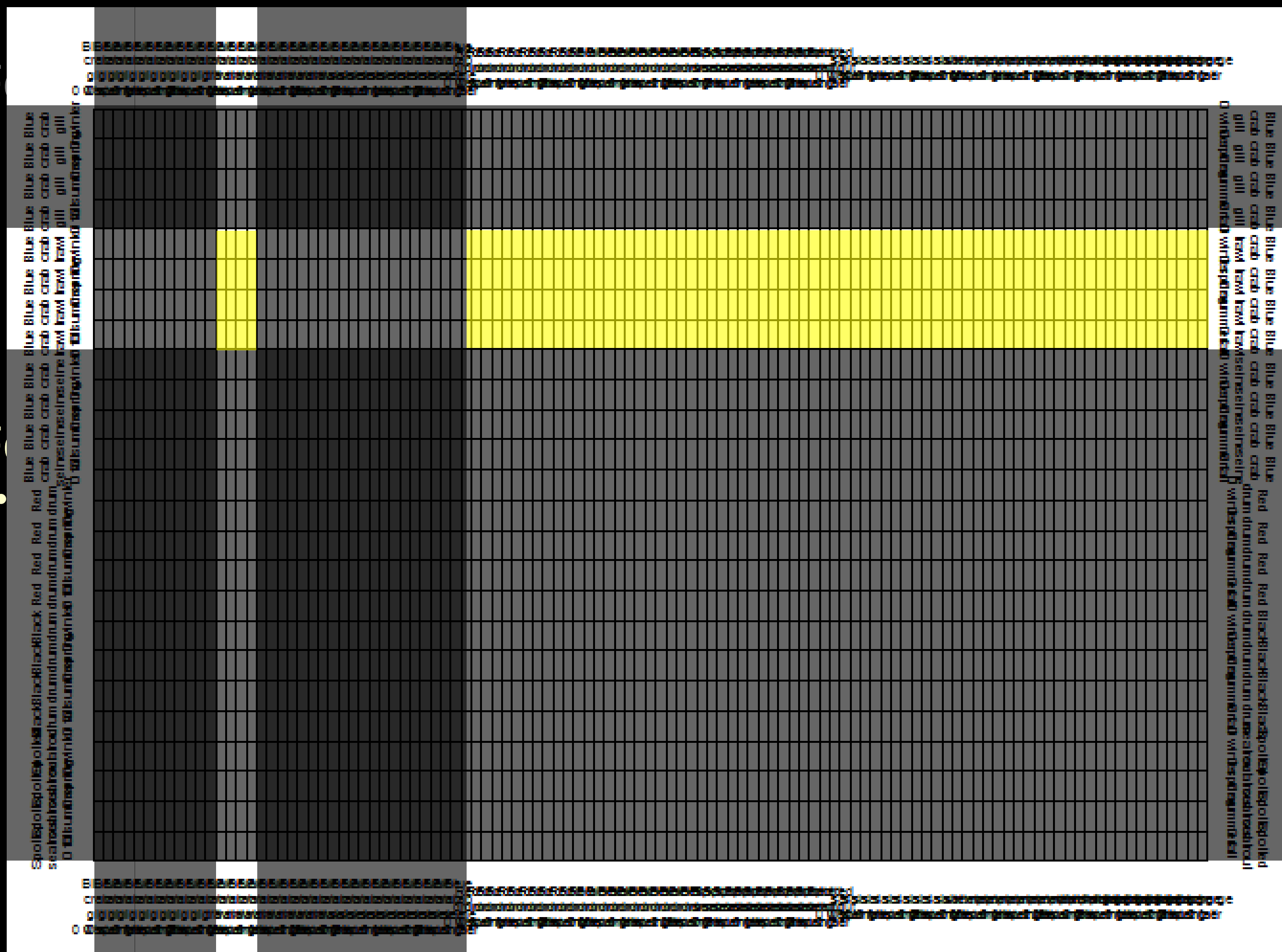
- Focus on trawl datasets for focal species predictors
  - Same reasons as above

Seasonal models

Models with 4 seasons & up to 2 year lags included



Seasonal models

Models with 4 seasons & up to 2 year lags included

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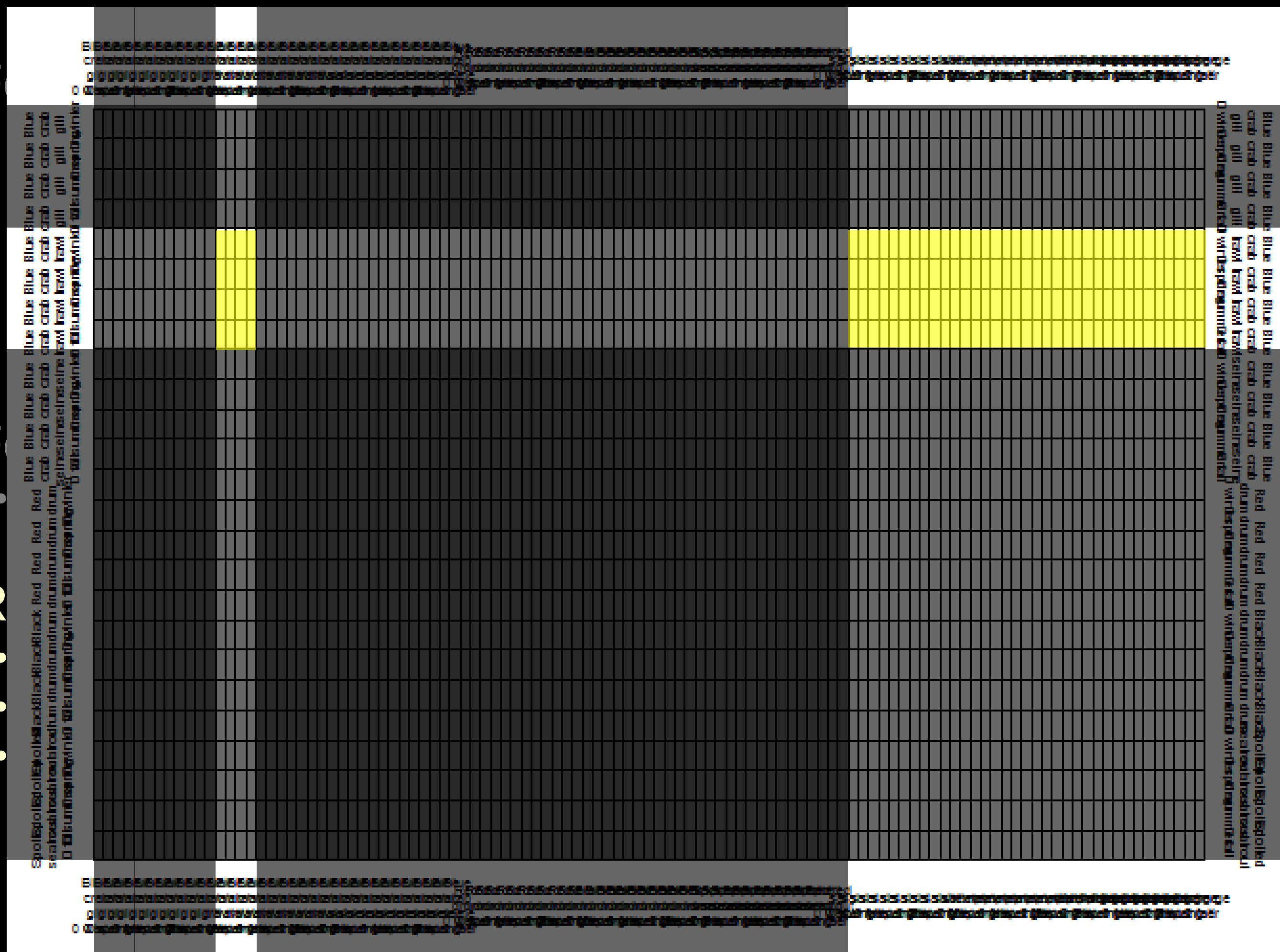
  - Trawl samples taken throughout bays rather than only along perimeters (gill net and seine samples)
  - Trawl samples taken year-round rather than only in spring and fall (gill net samples)
  - Most consistent and ecologically plausible results in original models
- Focus on trawl datasets for focal species predictors
  - Same reasons as above
- Remove predators as predictors
  - Gill net samples only taken in spring and fall
  - Influenced by FW inflows so would also have to be estimated
  - Removal has very little effect on model results

Seasonal models

Models with 4 seasons & up to 2 year lags included



Seasonal models

Models with 4 seasons & up to 2 year lags included

- Focus on trawl datasets for focal species responses
  - Trawl samples taken throughout bays rather than only along perimeters (gill net and seine samples)
  - Trawl samples taken year-round rather than only in spring and fall (gill net samples)
  - Most consistent and ecologically plausible results in original models

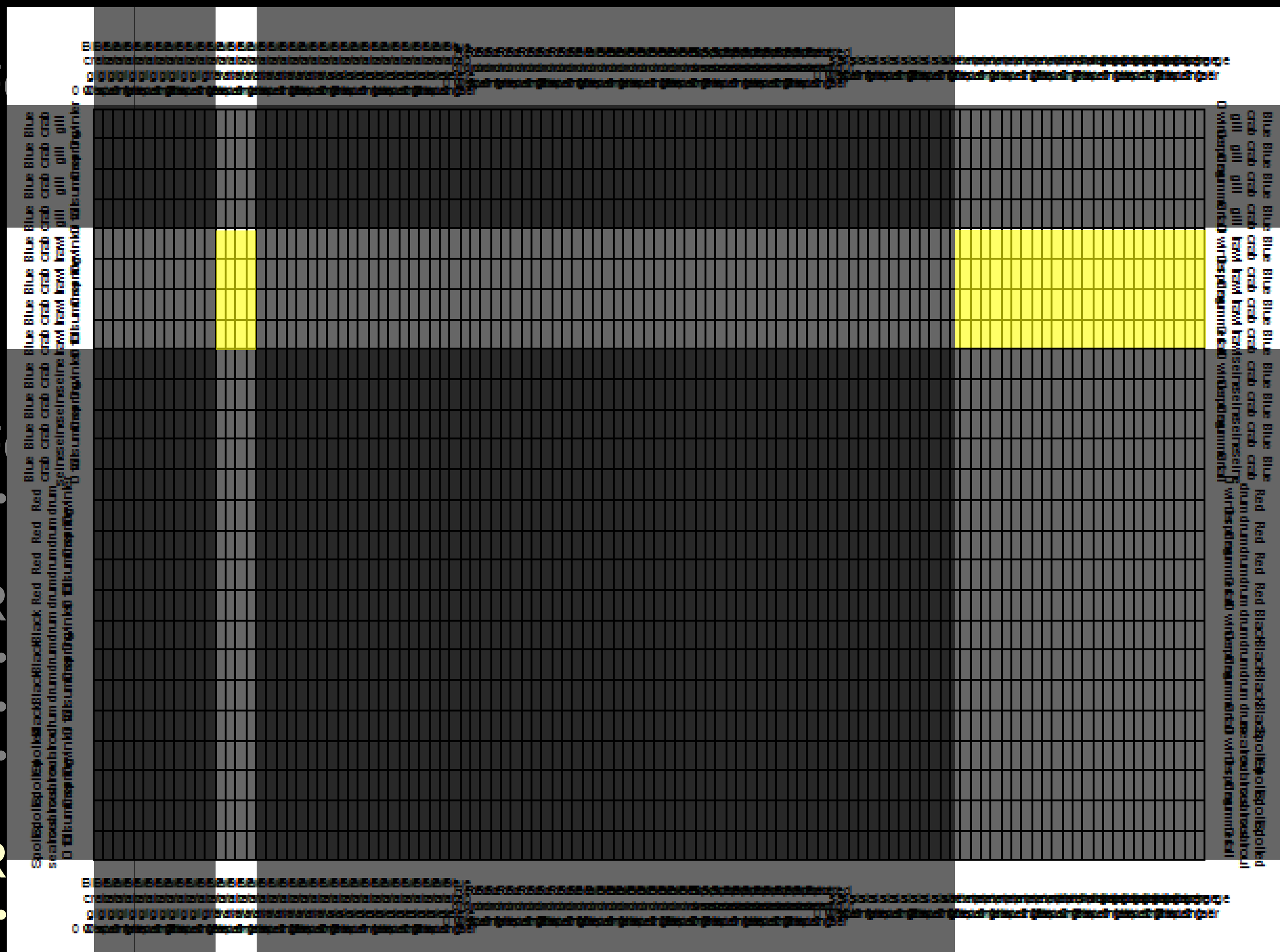
- Focus on trawl datasets for focal species predictors
  - Same reasons as above

- Remove predators as predictors
  - Gill net samples only taken in spring and fall
  - Influenced by FW inflows so would also have to be estimated
  - Removal has very little effect on model results

- Remove salinity as predictor
  - Would have to be estimated as a function of FW inflow

Seasonal models

Models with 4 seasons & up to 2 year lags included



Seasonal models

Blue crab (winter, spring, summer, fall)

	In Blue Crab t-1				In Discharge				Water Temperature			
	winter 0	spring 0	summer 0	fall 0	winter 0 -1 -2	spring 0 -1 -2	summer 0 -1 -2	fall 0 -1 -2	winter 0 -1 -2	spring 0 -1 -2	summer 0 -1 -2	fall 0 -1 -2
Blue crab winter				✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab spring	✓				✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab summer		✓			✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab fall			✓		✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓

Seasonal models

Blue crab (winter, spring, summer, fall)

- Use BIC to select best model

	ln Blue Crab t-1				ln Discharge				Water Temperature			
	winter 0	spring 0	summer 0	fall 0	winter 0 -1 -2	spring 0 -1 -2	summer 0 -1 -2	fall 0 -1 -2	winter 0 -1 -2	spring 0 -1 -2	summer 0 -1 -2	fall 0 -1 -2
Blue crab winter				✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab spring	✓				✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab summer		✓			✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab fall			✓		✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓

Seasonal models

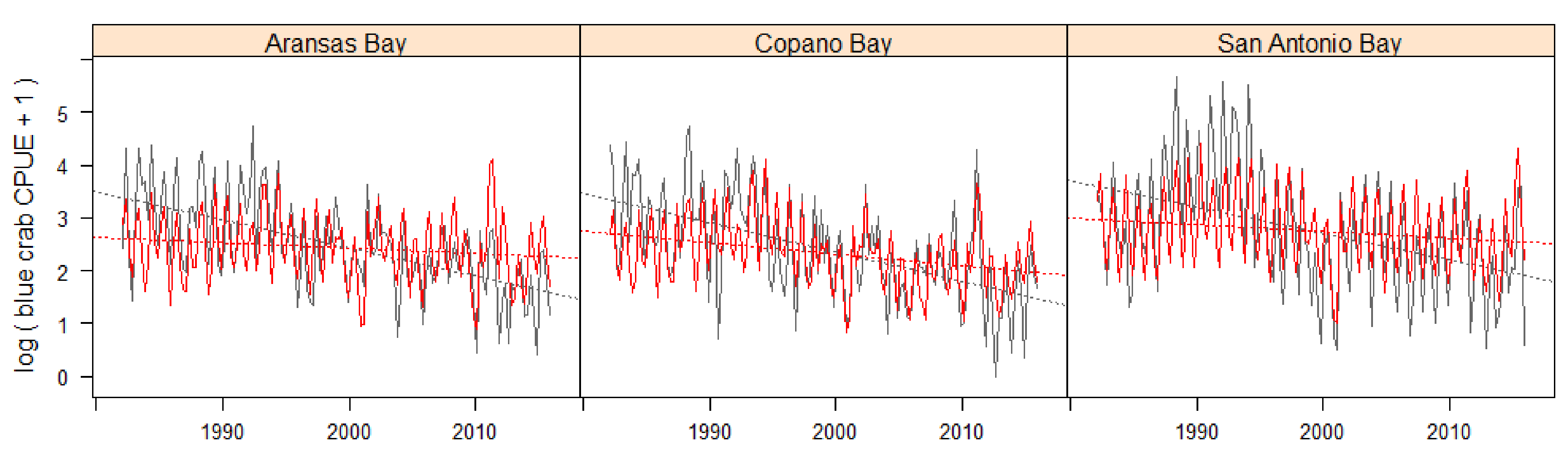
Blue crab (winter, spring, summer, fall)

- Use BIC to select best model
- Largest coefficients seen in winter model
    - High density dependence on preceding fall abundance
    - Positive effect of last winter's river discharge
    - Strong negative effect of summer temperature at 2 year lag

	In Blue Crab t-1				In Discharge				Water Temperature			
	winter 0	spring 0	summer 0	fall 0	winter 0 -1 -2	spring 0 -1 -2	summer 0 -1 -2	fall 0 -1 -2	winter 0 -1 -2	spring 0 -1 -2	summer 0 -1 -2	fall 0 -1 -2
Blue crab winter				**✓**	✓ **✓** ✓	✓ ✓ ✓	✓ ✓ ✓	**✓** ✓ ✓	✓ **✓** ✓	✓ ✓ ✓	✓ ✓ **✓**	✓ ✓ ✓
Blue crab spring	**✓**				✓ ✓ ✓	✓ ✓ ✓	**✓** **✓** ✓	✓ ✓ **✓**	**✓** ✓ ✓	✓ ✓ **✓**	✓ ✓ ✓	**✓** ✓ ✓
Blue crab summer		**✓**			✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	**✓** ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓
Blue crab fall			**✓**		✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ **✓** **✓**	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ **✓** ✓

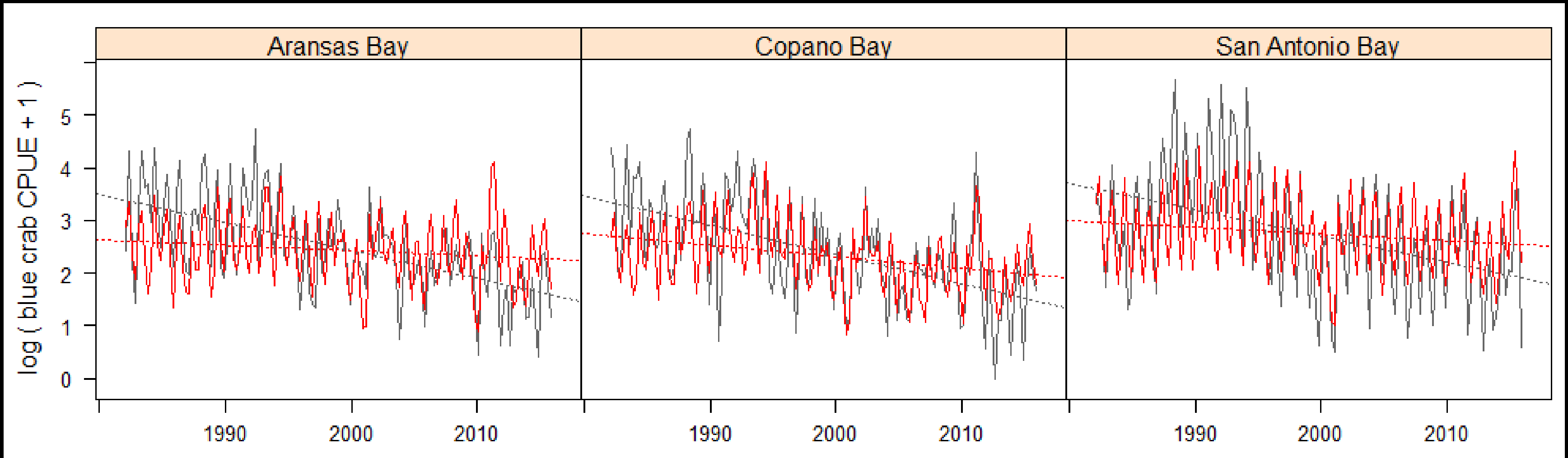
Seasonal models

Blue crab: original vs. predicted abundance trends

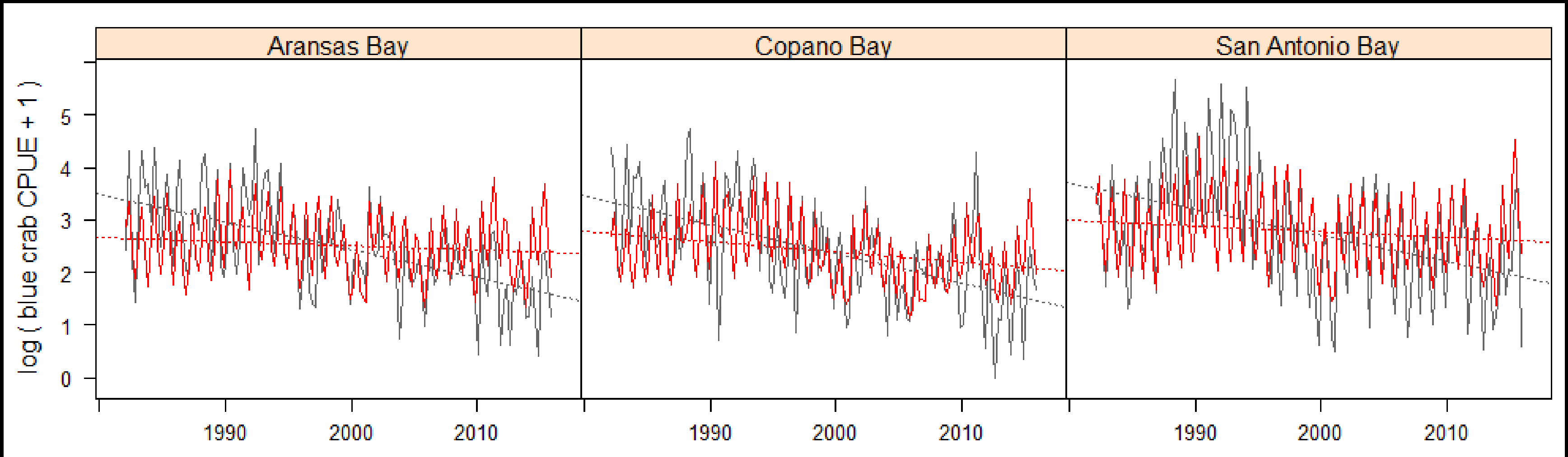


Seasonal models

Blue crab: original vs. predicted abundance trends

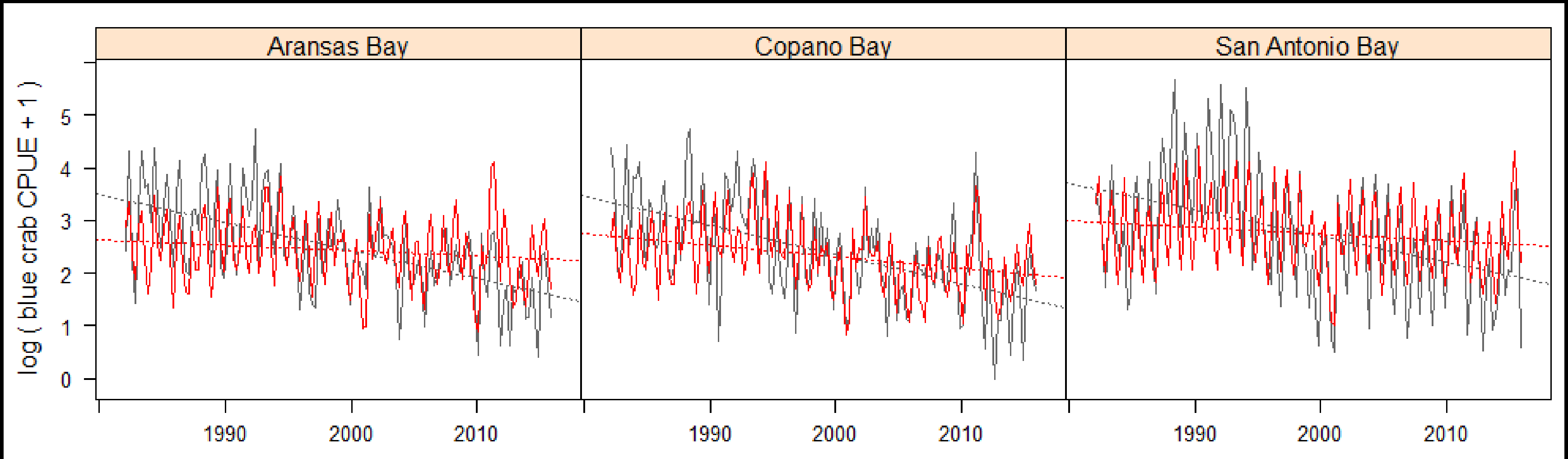


Effects of temperature on long-term trends (discharge set to seasonal means)

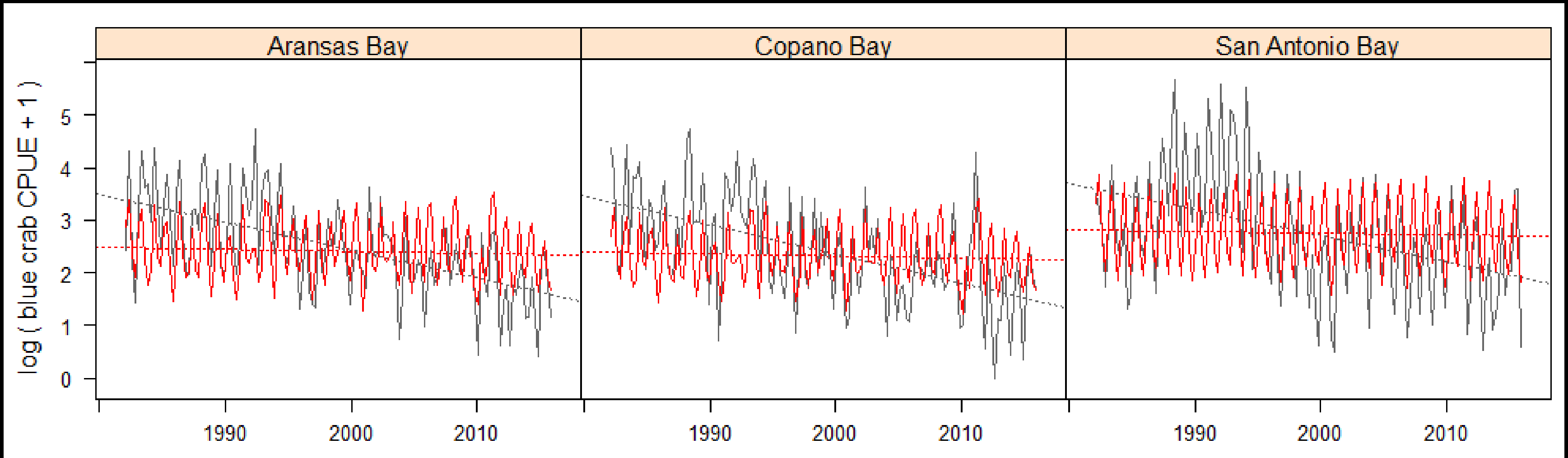


Seasonal models

Blue crab: original vs. predicted abundance trends



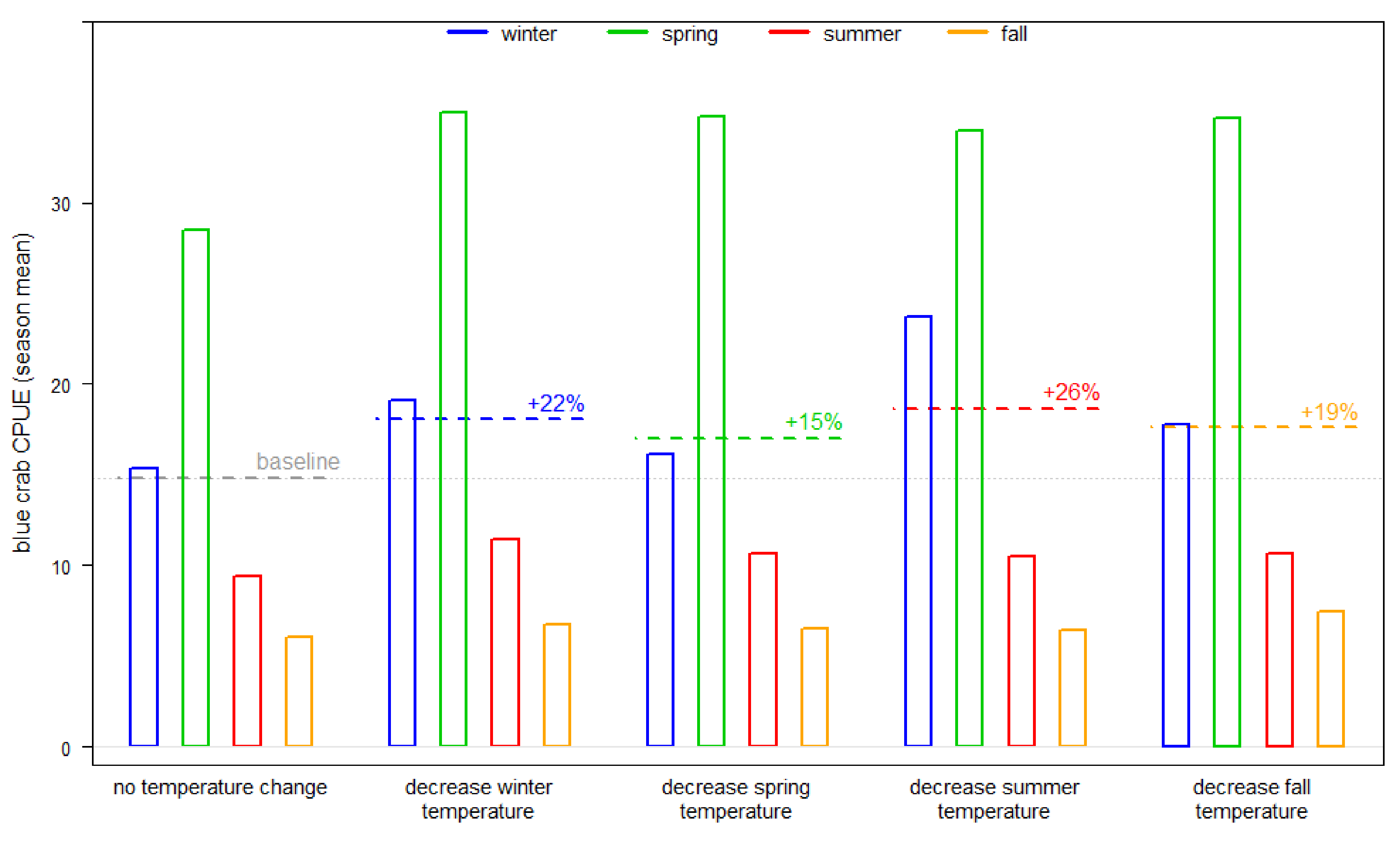
Effects of discharge on long-term trends (temperature set to seasonal means)



Seasonal models

Blue crab: seasonal and overall abundance changes

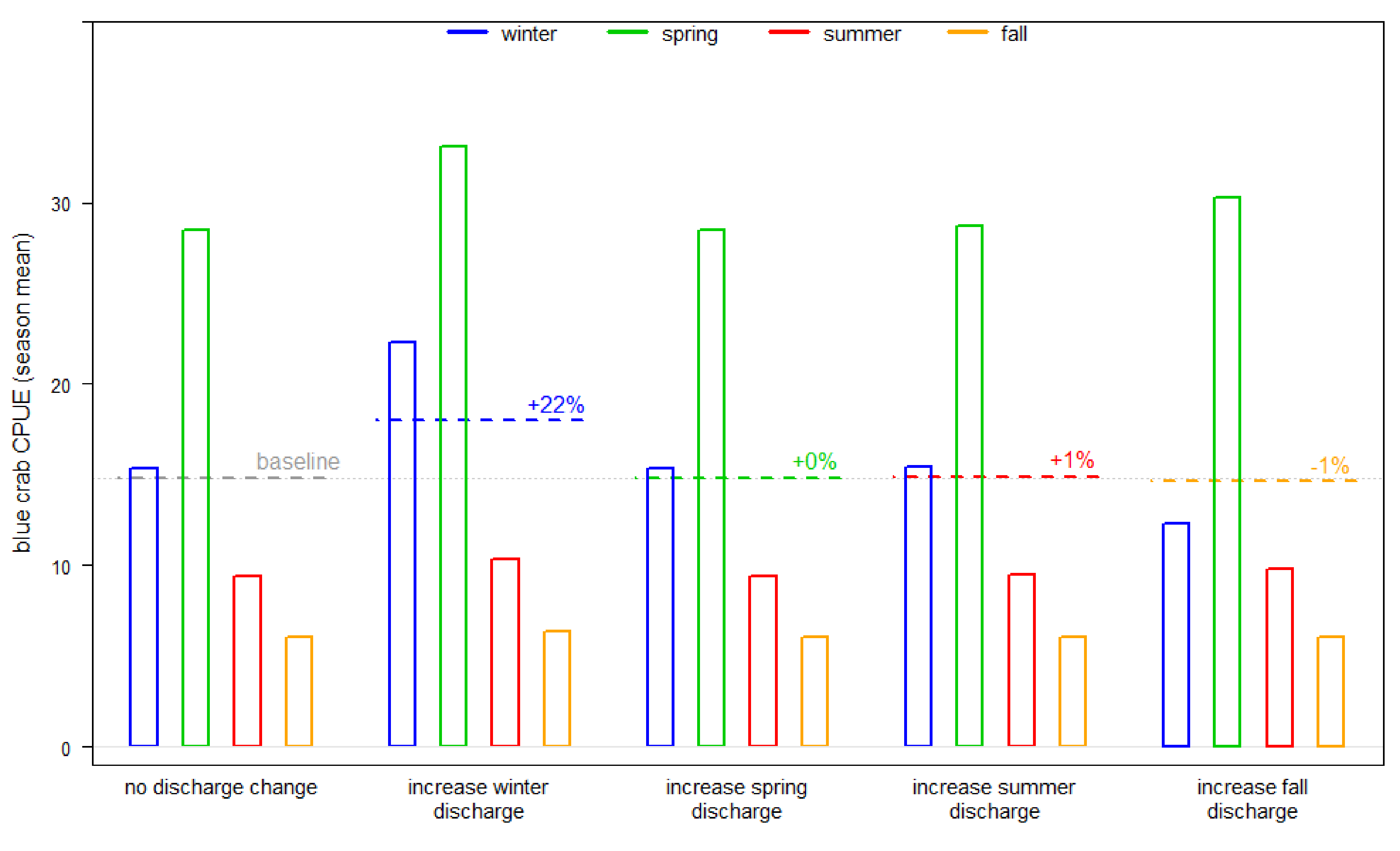
- **Decrease temperature 1°C each season**



Seasonal models

Blue crab: seasonal and overall abundance changes

- **Increase discharge 300% each season**



Seasonal models

White shrimp (winter, spring, summer, fall)

	In White shrimp t-1				In Discharge				Water Temperature			
	winter 0	spring 0	summer 0	fall 0	winter 0 -1	spring 0 -1	summer 0 -1	fall 0 -1	winter 0 -1	spring 0 -1	summer 0 -1	fall 0 -1
White shrimp winter				✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓
White shrimp spring	✓				✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓
White shrimp summer		✓			✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓
White shrimp fall			✓		✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓

Seasonal models

White shrimp (winter, spring, summer, fall)

- Use BIC to select best model

	ln White shrimp t-1				ln Discharge								Water Temperature							
	winter	spring	summer	fall	winter		spring		summer		fall		winter		spring		summer		fall	
	0	0	0	0	0	-1	0	-1	0	-1	0	-1	0	-1	0	-1	0	-1	0	-1
White shrimp winter				**✓**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	**✓**	✓	✓	✓	✓
White shrimp spring	**✓**				**✓**	✓	✓	✓	✓	✓	✓	✓	**✓**	**✓**	✓	✓	✓	✓	✓	✓
White shrimp summer		**✓**			✓	*✓*	✓	**✓**	**✓**	✓	✓	**✓**	✓	✓	✓	✓	✓	✓	✓	✓
White shrimp fall			**✓**		✓	✓	✓	✓	**✓**	✓	✓	✓	✓	✓	✓	✓	*✓*	✓	✓	✓

Seasonal models

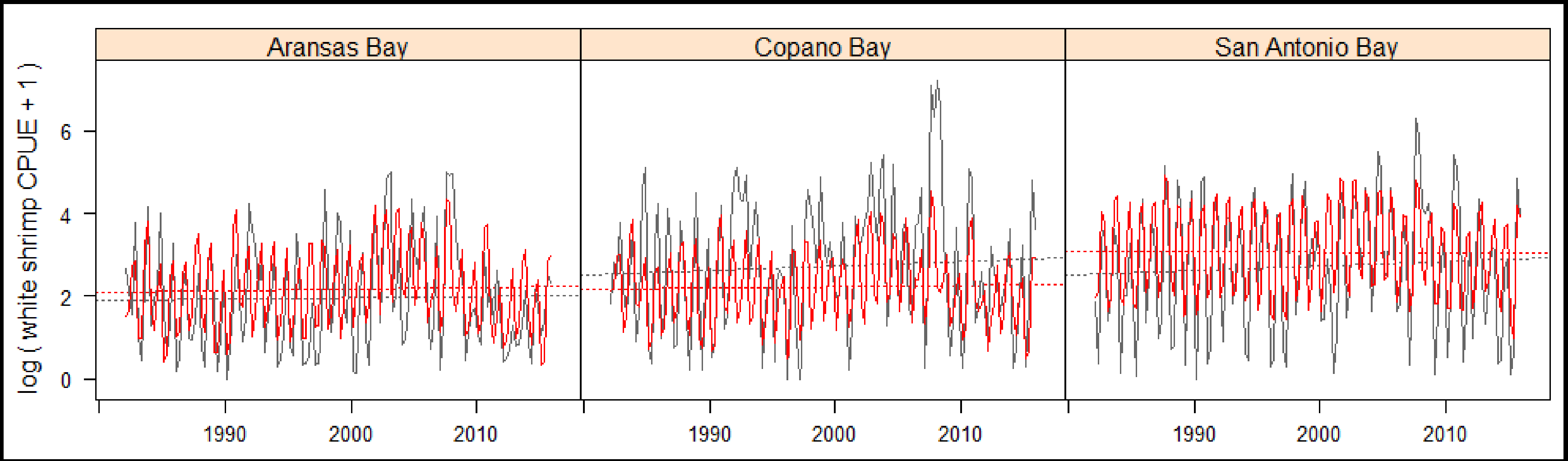
White shrimp (winter, spring, summer, fall)

- Use BIC to select best model
- Largest coefficients
  - High winter density dependence on preceding fall abundance
  - Negative effect of preceding year’s winter discharge on summer abundance
  - Positive lag-0 effect of river discharge on summer abundance
  - Negative effect of preceding summer’s temperature on fall abundance

	ln White shrimp t-1				ln Discharge				Water Temperature			
	winter 0	spring 0	summer 0	fall 0	winter 0 -1	spring 0 -1	summer 0 -1	fall 0 -1	winter 0 -1	spring 0 -1	summer 0 -1	fall 0 -1
White shrimp winter				**✓**	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ ✓	✓ **✓**	✓ ✓	✓ ✓
White shrimp spring	**✓**				**✓** ✓	✓ ✓	✓ ✓	✓ ✓	**✓** **✓**	✓ ✓	✓ ✓	✓ ✓
White shrimp summer		**✓**			✓ **✓**	✓ **✓**	**✓** ✓	✓ **✓**	✓ ✓	✓ ✓	✓ ✓	✓ ✓
White shrimp fall			**✓**		✓ ✓	✓ ✓	**✓** ✓	✓ ✓	✓ ✓	✓ ✓	**✓** ✓	✓ ✓

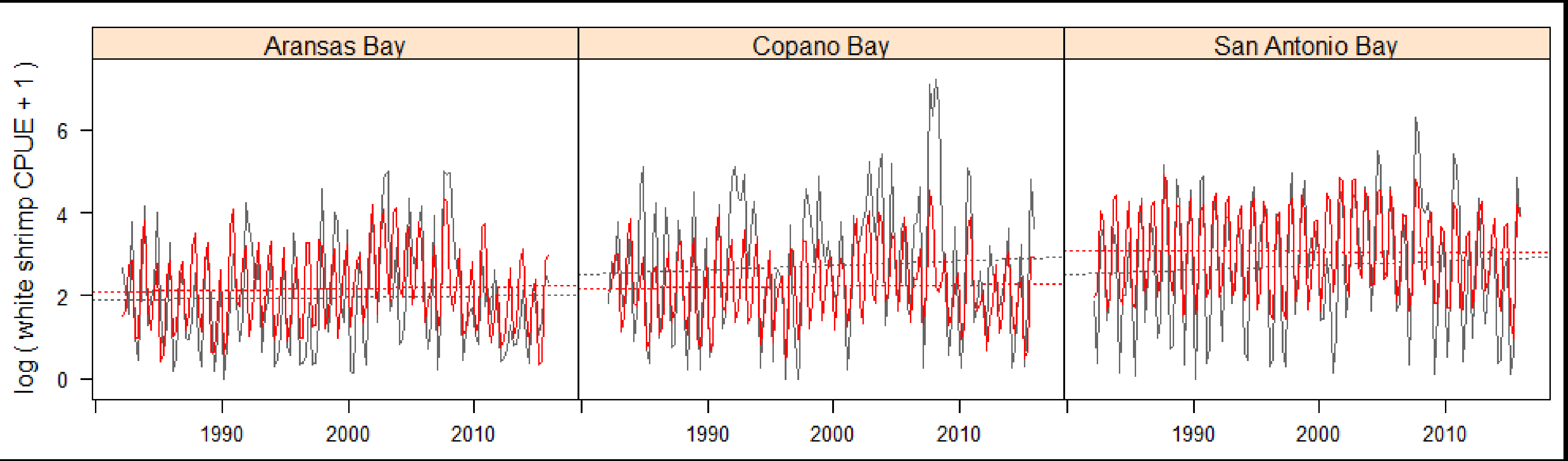
Seasonal models

White shrimp: original vs. predicted abundance trends

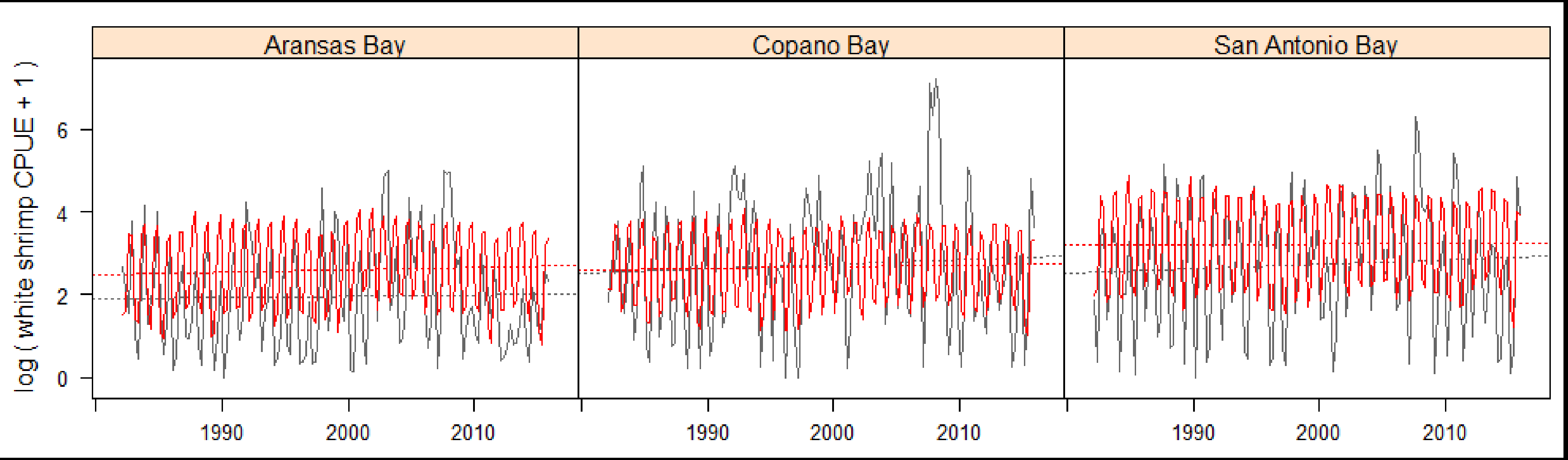


Seasonal models

White shrimp: original vs. predicted abundance trends

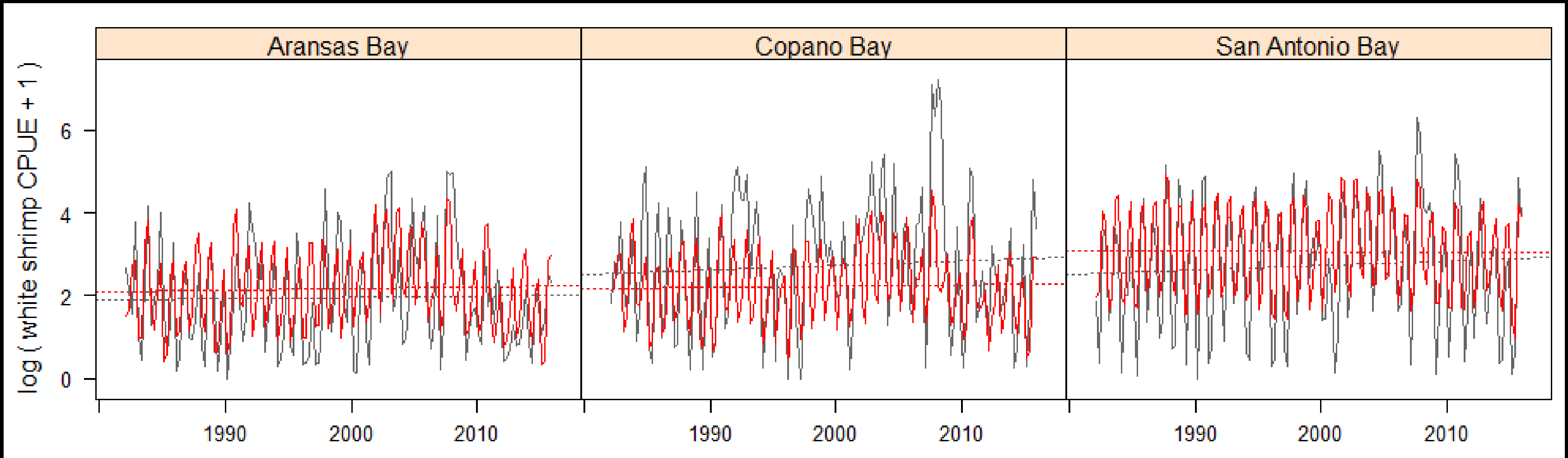


Effects of temperature on long-term trends (discharge set to seasonal means)

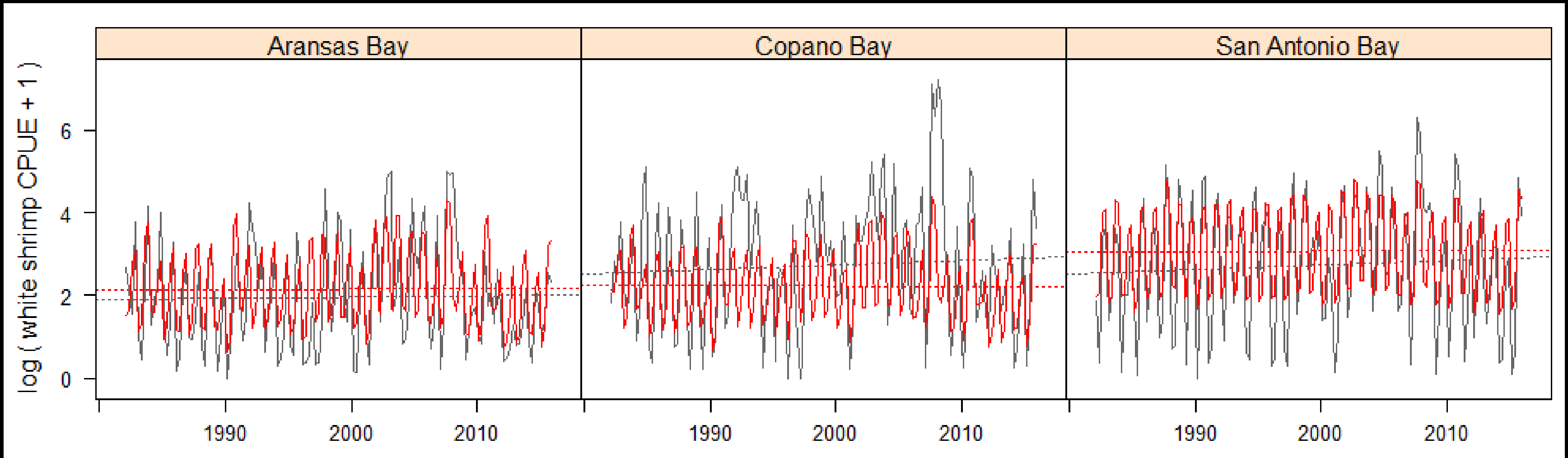


Seasonal models

White shrimp: original vs. predicted abundance trends



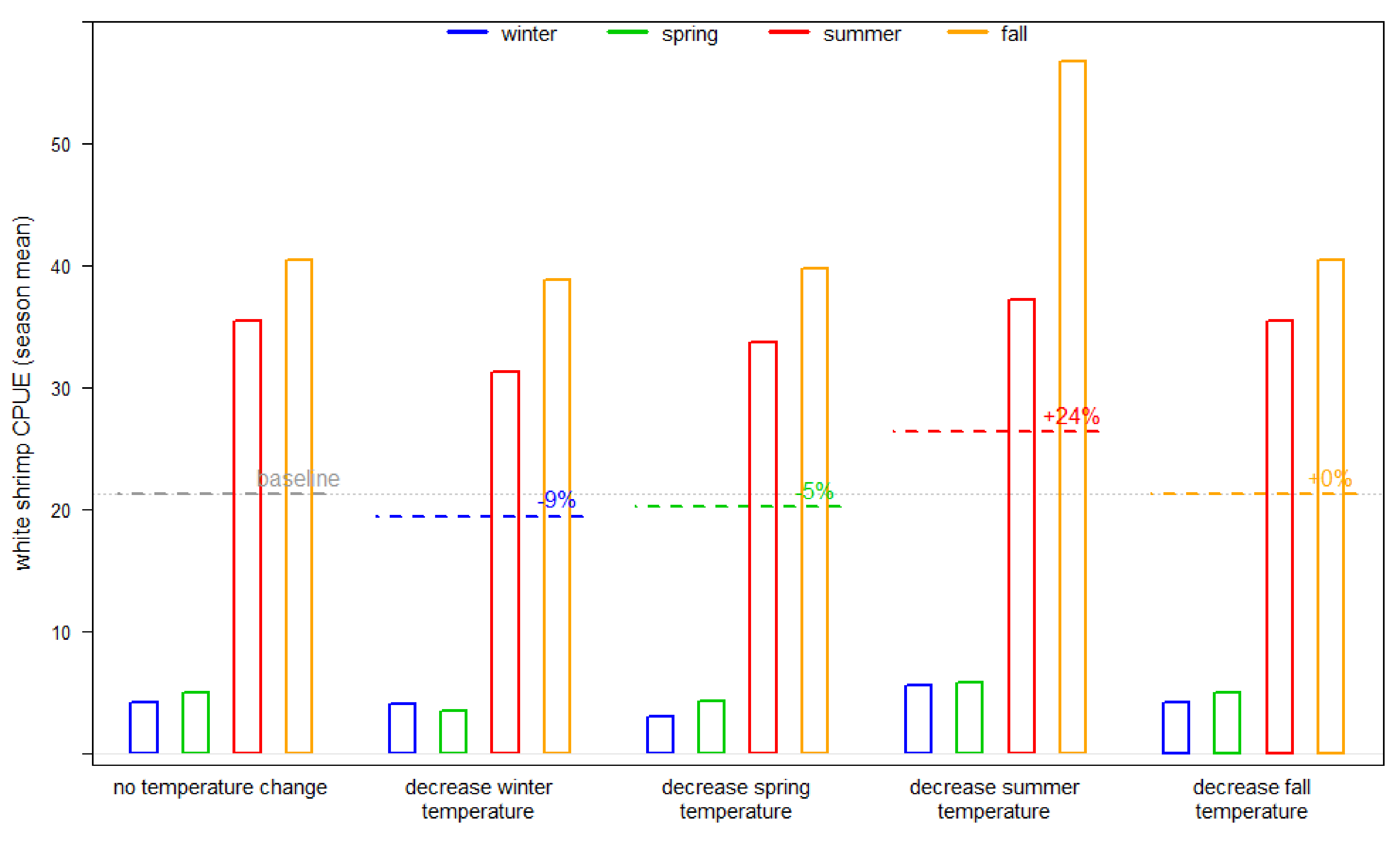
Effects of discharge on long-term trends (temperature set to seasonal means)



Seasonal models

White shrimp: seasonal and overall abundance changes

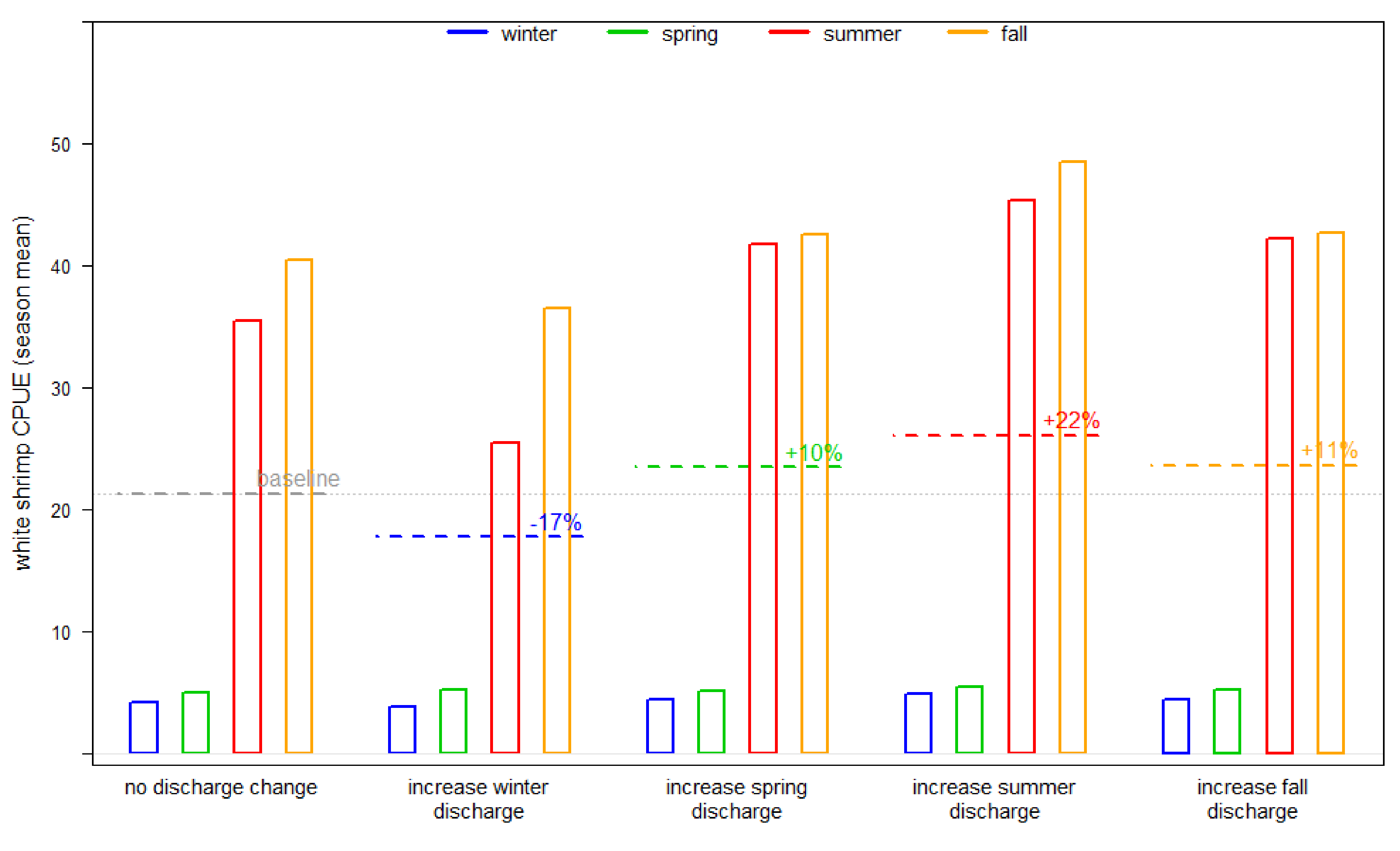
- **Decrease temperature 1°C each season**



Seasonal models

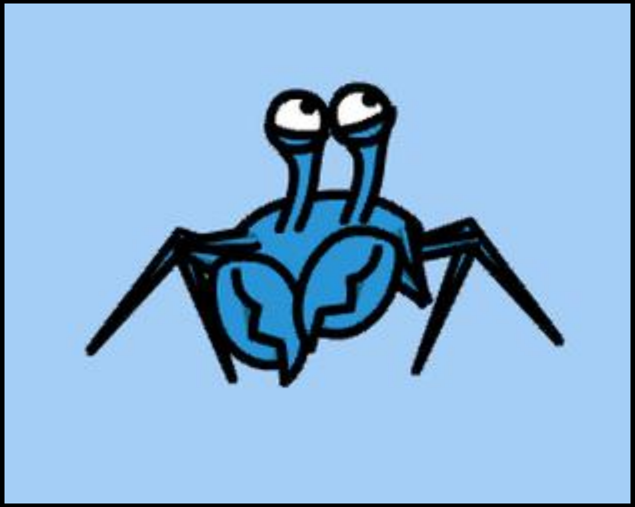
White shrimp: seasonal and overall abundance changes

- **Increase discharge 100% each season**



Summary

- Original model structure from phase 1 needed to be altered to accommodate multiple seasons of each variable in the analysis
- Predictor variables affected by FW inflows were omitted to avoid using estimated values to predict focal species abundances
- Model results:
  - Temperature
    - High summer temperatures negatively affect both blue crab and white shrimp abundances
  - Freshwater inflows
    - Large increases in winter river discharge are needed to see positive impacts on blue crab abundance
    - Summer river discharge positively affects white shrimp abundances



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